Entrepreneurship, Innovation and Competition

Empirical Evidence for Germany

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Abbreviations

BIC	Bayesian Information Criterion
cdf	cumulative distribution function
CEO	Chief Executive Officer
CIS	Community Innovation Survey
cloglog	Complementary log-log model
Commission	Commission of the European Communities
DPMA	German Patent and Trademark Office (Deutsches Patent- und Markenamt)
EPO	European Patent Office
EU	European Union
FIML	Full-information maximum likelihood
GDP	gross domestic product
GDR	Former German Democratic Republic
IPO	Initial Public Offering
IV	Instrumental variable
KfW	Kreditanstalt für Wiederaufbau
LR test	Likelihood ratio test
MIP	Mannheim Innovation Panel (see description in Appendix A.1)
ML	maximum likelihood
NACE	Nomenclature of economic activities = 5-digit industry classification (Nomenclature générale des activités économiques)
Negbin	Negative Binomial
OECD	Organisation for Economic Co-operation and Development

OLS	Ordinary least squares
p.	page
pp.	pages
PATSTAT	EPO Worldwide Patent Statistical Database
R&D	research and development
RoS	return on sales
SCP	Structure - Conduct - Performance
SME	small- and medium-sized enterprize
TFP	total factor productivity
U.S.	United States of America
VC	venture capital
VCC	VC companies
wrt	with respect to
ZEW	Zentrum für Europäische Wirtschaftsforschung (Centre for European Economic Research)
ZEW-FP	ZEW Foundation Panel (see description in Appendix B.2)
ZEW-HF06	ZEW Hightech Founders Survey 2006 (see description in Appendix B.2 and Chapter 3)
ZINB	Zero-inflated Negative Binomial
ZIP	Zero-inflated Poisson
ZIP code	postcode for a small regional area

1. Introduction

The current debate about competitive innovative firms, Europe's lack of "gazelles" and its technological gap with respect to the United States (U.S.) is mainly based on the observation of few enterprizes which were able to grow substantially in terms of employment and which gained a leading position in the generation of new knowledge and markets within the first years after their emergence, e.g. Microsoft. Generalizing this anecdotic evidence, young and innovative firms are supposed to contribute to competitiveness, structural change, adoption and diffusion of technological know-how (see e.g. Nerlinger (1998)).

This observation has also reached the political debates, particularly on the European level. Becoming the most competitive and most dynamic knowledge-based economy in the world is the main aim of the so-called Lisbon Agenda launched by the Council of the European Union (EU) in the year 2000. The outlined strategic goals are aimed at sustainable growth and the creation of new and superior employment opportunities. Already in 1988, Scherer (1988) stated to the U.S. Congress "The question of innovation is particularly important, for upon the innovativeness of our industries depends on productivity growth, which in turn has a critical bearing on the rate at which material standards of living advance." In a nutshell, this underlines that the success of an economy in generating innovation and technological advances should translate into increasing growth of productivity, which affects international competitiveness (Audretsch, Yamawaki (1988)).

The comprehensive strategy to achieve the Lisbon Agenda, substantiated by the Barcelona objectives in the year 2002, includes manifold elements (European Council (2000)). Two major elements are innovation and small- and medium-sized enterprizes (SMEs). Regarding innovation, the famous 3 % goal, targeting at the research and development (R&D) expenditures per gross domestic product (GDP), has been launched. But the technological gap between Europe and the U.S. did not diminish since 2000, and R&D investments at the level of the EU did not augment to the adopted target. In contrast, during the years 2000 to 2006 the R&D intensity did not increase, and also the second Barcelona objective – R&D investments by companies should rise up to 2 % – was not met as it still remains under 1 %. Guellec and Sachwald (2008) claim that a substantial number of high-tech start-ups would help to catch up. But they identify that the creation of start-ups in high-tech sectors is insufficient in the European Union. Moreover, compared to their U.S. counterparts, European SMEs are characterized by lower productivity and slower growth. For example, the number of employees in U.S. SMEs increased by 60 % within seven years after their foundation whereas in Europe the growth ranges between 10 to 20 % (Commission of the European Communities (2008)).

The importance of innovative entrepreneurship for the creation of new industries and the economy's competitiveness is clarified if we look at the development of emerging markets in the U.S. which was mainly driven by emerging businesses. Today's global players in those markets already appeared during the initial stage of the industry. In contrast, European high- and medium-tech firms are generally long-established large companies or niche market leaders of medium size. Thus, the conquest of new high-tech markets often rests upon incumbents responding to international competition and new opportunities. Ironically, this process of accessing new technology markets oftentimes begins with the acquisition of high-tech start-ups originating from the U.S. Guellec and Sachwald (2008) summarize this effect as "industrial restructuring process that was operated through markets in the United States occurred within companies in Europe".

Another contribution of new (or potential) entrants is to increase the competitive pressure on incumbents and cause them to behave less opportunistically. By entry (threat), they may also force the incumbents to increase innovation investments in order to keep up with the technological development and strengthen their market position. Hence, young innovative firms are assumed to directly – via own funds – and indirectly – by forcing incumbents to augment the R&D investments via increasing competitive pressure – contribute to an augmentation of business R&D expenditures, the second Barcelona objective (Guellec, Sachwald (2008)).

In the economic literature, the drivers of innovation and technological change are discussed, e.g. whether large or entrepreneurial firms more substantially contribute to innovation. Schumpeter (1934, 1939, 1942) was one of the first to link innovation, entrepreneurship and technological change. His views are the basis for two streams of research: The first outlines the importance of new ventures by individual entrepreneurs, and the second stresses the role of corporate entrepreneurship in the renewal of large firms. Relying on Schumpeter (1934) the first strand emphasizes the role of the entrepreneur in carrying out innovation and technological change. The second stream of research is based on Schumpeter (1949) where he states that the entrepreneur need not be a physical person but is seen in terms of the function in a company. Consequently, large firms might be the drivers of innovation because they have the resources and capital to invest in R&D activities (Hagedoorn (1996)). Both statements seem to be somewhat contradictory, but reflect the current situation to a certain extent: Whereas the "early Schumpeter" can be applied to many examples of the emergence of new industries in the U.S. the "late Schumpeter" reflects how European firms mainly adopt new technologies and enter innovative markets.

Baumol (2002) claims that the difference between innovation in large and entrepreneurial firms is that breakthrough innovations are provided by the entrepreneur whereas the innovation process carried out by large, established firms is more routinized and often enhances the breakthroughs by making them more useful. Hence, innovation by entrepreneurial and large firms are complementary. A similar point of view is taken by Acs and Grifford (1996). They postulate that as firms grow, new product innovations become less important than maintaining profitability by building up new product lines. Acknowledging that the average innovation in large firms is of higher quality, Cohen and Klepper (1992) state that large firms and basic research institutions constitute the scientific and technological basis for major innovation whereas technological opportunities are exploited and commercialized by small innovative firms.

This thesis presents empirical work on three central aspects of industrial organizations which are also part of the Lisbon strategy: Entrepreneurship, innovation and competition. More precisely, it addresses different aspects of the emergence of new firms. There may be two different points of viewing emerging firms. First, the competition literature looks at potential or actual market entry by new or established firms and the barriers to it. In the center of interest are market and competition characteristics like strategic behavior of incumbents. Strategic behavior includes the building up of barriers to entry, e.g. by innovation or advertisement (see e.g. Sutton (1991), Bain (1956)). From the competition point of view, market entry contributes to the dynamics of industries, hence it may influence the competitive situation and force incumbent firms to behave more competitively.

Second, in the entrepreneurship literature, entrants or potential entrants are subject to a closer look at the occurrence of firm creation and the constraints of establishing a new firm beyond entry barriers. That means that the entrepreneurship literature focuses on what may foster or impede the creation of firms at the individual level, what are the main drivers of successful entrepreneurship and what are the motives for starting a new business. Market structure and competition are two among many factors. The effects of newly founded firms on competition are usually not considered.

The first part of this dissertation focuses on competition and the effect of potential market entry on the conduct of incumbent firms. Using survey data we are able to identify the threat of entry as it is perceived by the firms. In the absence of actual entry, the threat of the market position by potential entrants is supposed to have disciplinary effects on the behavior of incumbents leading to lower price setting power and hence lower margins (Baumol et al. (1982)). Besides threat of entry, we consider barriers to entry and their effect on the optimal number of competitors in a market. We predict in a theoretical model that the optimal number of competitors decreases with the extent of entry barriers. This prediction is tested.

Aside, in Section 2.2, we conduct an investigation of how good standard concentration indices reflect the market structure on the relevant market. Therefore, we compare them to competition variables taken from survey data based on the perception of the interviewed firms. As a result, standard concentration indices relying on industry definition do not seem to be able to accurately reflect the relevant market and the related competitive situation of the firm. In line with this result, we do not use standard concentration indices but survey data on competition issues in our analyses of the threat of and barriers to entry discussed in the previous passage.

Chapter 3 deals with entrepreneurship and a particular "barrier to entry" for young firms: The lack of finance. Many studies find that a crucial factor to successful firm creation and evolution is access to adequate financial resources. But particularly for young high-tech firms, a so-called funding gap exists, i.e. limited access to financial markets. Two forces are responsible for the funding gap: First, innovative firms, primarily young firms, may have difficulties in finding investors because of their inherent risk and substantial information asymmetries. Second, innovative firms, particularly in manufacturing, usually need a large amount of funds at the early stages (Gompers (1993)) for sunk investments, e.g. in machinery or salaries for qualified employees. As discussed in Section 3.2.2, venture capital (VC) is often seen as a last resort for this kind of entrepreneurs because those investors search for high-risk and potentially high-rewarded investment opportunities. Besides capital, they also provide support, and are often actively involved in the firms. As the portfolio firms are in general not able to provide substantial collaterals and are active in highly risky environments, the active involvement is one means to reduce information asymmetries.

The second part of the dissertation is divided in two sections which both deal with the impact of VC investors on specific firm decisions. The first section (see Section 3.4) looks at changes in the top management team. The right to push for executive turnover is often part of the contract concluded between the VC investor and its portfolio firm. Therefore, the influence of VC financing regarding changes in the founding executive team is investigated. In a second step, the impact of VC financing on the timing of changes is considered. And finally, the impact of changes – whether induced by VC investors or not – regarding firm performance measured as firm growth in terms of employment and labor productivity is tested.

Based on the observation that many "gazelles" in highly innovative markets have been VC-financed when starting their business (e.g. Microsoft, Apple), Section 3.5 deals with the impact of VC financing on firms' innovation activities. Whereas innovation is represented by patenting activity and a new variable called innovativeness reflecting the degree of firms' innovation.

Finally, Chapter 4 takes a closer look at the persistence of firms' innovation activities. We link the dynamics of innovation behavior to business cycle fluctuations. Usually, it is assumed that innovation, and particularly, R&D expenditures follow a smooth path. But according to Schmookler (1966), innovation may be responsive to fluctuations in market demand. We look at indicators of economic activity and their impact on firms' innovation decision. Furthermore, we test whether SMEs' innovation decisions are more vulnerable to business cycle fluctuations.

2. Competition and profitability

This chapter presents joint work with Kornelius Kraft and deals with competition issues. Section 2.1[1] links threat of and barriers to entry to firms' profitability. Furthermore, it is tested whether the number of competitors in a market is determined by entry barriers. In Section 2.2[2], we investigate the usefulness of standard concentration indices as indicators for the market structure and claim that in this case survey-based indicators of firms' competitive situation may be more suitable to depict the situation on the relevant market.

2.1. Barriers to entry, firms' profitability and number of firms

2.1.1. Introduction

The observation of short-run high profits is not incompatible with the existence of a long-run competitive equilibrium. Prospective high profits are needed to provide incentives for innovation or any other activity to improve the efficiency of a firm. However, it is expected that in the long-run excessive profits are competed away by reactions of the present competitors, and furthermore, that high profits attract entry, which is particularly important if the highly profitable firm has a dominant position and holds a large market share.

In light of the mechanisms by which markets adjust, the absence of barriers to entry is fundamental for economic welfare. It is necessary that a situation of considerable mar-

[1] This section has been published as ZEW Discussion Paper: Heger, D. and K. Kraft (2008), *Barriers to entry and profitability*, ZEW Discussion Paper 08-071.

[2] This section has been released as ZEW Discussion Paper: Heger, D. and K. Kraft (2008), *A test of the quality of concentration indices*, ZEW Discussion Paper 08-072.

ket power with high profits attracts entry by challengers and that by this intensification of the competitive pressure the profits adjust to a "normal" level.

Economic theory has discussed extensively the conditions for barriers to entry and the effects thereof. Although there is no consensus about the exact definition of what a barrier to entry actually is, it is undeniable that barriers to entry play an important role in a wide variety of competition issues. Entry barriers can retard or even entirely prevent the working of a market and welfare may be seriously affected by them.

There are quite a few empirical studies on the determinants of barriers to entry and also some on the effects of entry on profitability or other variables of interest, e.g. innovation. Martin (2002, p. 221) notes: "Another such strand is the argument, going back to Bain (1956) and recently re-emphasized by Baumol et al. (1982), that market performance depends in an essential way on the importance of potential entry. The problem this raises for econometric work is that potential entry is an unobservable variable." Usually, the effects of entry are identified by the realized entry of challengers. However, Martin (2002, p. 221) argues this is not a convincing way to model potential entry, as most actual entry is short and unsuccessful.

Our contribution is a different one: We investigate the effect of threat of entry. Information from managers, on their perception of how strong their own competitive position is threatened by a likely entry of competitors into their main markets, is applied to estimate what effect this threat of entry has on profitability. Aside of the value of using information on the perceived threat of entry we are able to identify the relevant markets as assessed by the managers themselves. In a second step, we model the influence of barriers to entry on the optimal number of competitors in a market and predict that fixed costs – as a proxy for barriers to entry – reduce the optimal number of firms in a market. This model is empirically tested.

The next section provides some general theoretical considerations about barriers to entry. Section 2.1.2.2 presents a theoretical model linking barriers to entry and the optimal number of firms in a market. The following sections are dedicated to the empirical implementation: Description of the data set, descriptive statistics, estimation strategy and results. Section 2.1.5 concludes this section.

2.1.2. Theoretical considerations

2.1.2.1. Barriers to entry

Entry and exit conditions are important factors that determine existing firms' possibilities to exert market power. A dominant firm with a very high market share might not be able to make use of its position, if any significant deviation of the price from marginal costs will lead to entry by new competitors. Entry by new firms can also affect innovativeness and put pressure on the existing firms not only to refrain from misusing their market power, but also to operate as efficiently as possible. Therefore, cost conditions might also improve. Hence, market shares and concentration are just one part of the story. In addition, the conditions for potential competition are important contributors to the functioning of markets.

A firm deciding whether to penetrate a market or not compares the benefits and costs of entry. The benefits are the expected profits and growth of demand connected with entry. The costs are, among other things, determined by barriers to entry, which may be caused by exogenous factors like economies of scale[3] or by strategic factors like excess capacity, limit pricing or advertising.

In the literature, the first important contribution to the discussion of entry barriers is Bain (1956). Following this, a lively debate took place which, however, did not succeed in finding a generally accepted definition. Bain defined a barrier to entry by its effects on profitability, in particular in terms of the ability to earn above-normal profits without inducing entry. Stigler (1968) later defines an entry barrier as a cost advantage of incumbents over entrants and von Weizsäcker (1980) argues that a cost differential is only an entry barrier if it reduces welfare (see McAfee et al. (2004) on this issue).

The discussed reasons for barriers to entry are manifold. Economies of scale may or may not be regarded as entry barriers. Clearly, with large scale economies there is only place for a few producers in an industry, and thus entry might be difficult. However, in the view of Baumol et al. (1982) it is the nature of the cost structure which determines entry barriers. In the absence of sunk costs, entry is not impeded and every firm presently active in the industry is disciplined by potential entry. Therefore, prices will

[3] Whether this really is a barrier to entry is debated.

be close to average costs. The problem is that in most industries a part of the costs will always be sunk.

Excess capacity plays an important role in the theoretical discussion. Spence (1977), Dixit (1979, 1980) and Bulow et al. (1985) are among the first to point out the asymmetry of an incumbent and a potential entrant. Typically, in such models the incumbent selects a level of capacity in the first period, and the potential entrant and the incumbent simultaneously determine quantities in the second period. These models assume that the incumbent produces at or below the capacity limit in the second period, and that the incumbent's marginal costs are lower than the potential entrant's marginal costs because the incumbent is able to avoid the costs associated with expanding capacity in the second period. Hence, the incumbent enjoys a first mover advantage.

Another cause of entry barriers is product differentiation. Consumers view products as imperfect substitutes for a number of reasons, such as different varieties (horizontal product differentiation) or product quality (vertical product differentiation). If introducing a new brand is connected with significant fixed costs, horizontal product differentiation may well lead to persistent entry barriers. Shaked and Sutton (1982, 1983) analyze a game where firms choose whether to enter at the first stage of the game, choose quality at the second stage and prices at the third stage. Surprisingly, they show in their model that only a few and at the limit only one firm will operate in the industry despite of free entry.

Obviously, firms have an interest in product differentiation, and they will attempt to increase the perceived difference or quality advantage of their products by the use of advertising. Advertising intends to increase consumers' loyalty to specific brands, and therefore to deter entry. Clearly, advertising expenditures are sunk costs and can as such increase the impediments to enter a market. This is the way advertising is introduced into the Sutton (1991) model. It can, however, also be argued that advertising informs consumers about the existence and the characteristics of new products, and thus, eases entry.

Another possible way of incumbents to raise entry barriers is by innovation. Bain (1956) already identifies absolute cost advantages as a major reason for entry barriers, and obviously, process innovation that aims at cost reductions. Secondly, newly developed products will lead to (at least temporary) advantages compared to competitors and therefore R&D activities can lead to reduced entry. At this point, it can also be argued in the opposite direction, as many entering firms are new foundations of innovators, who want to benefit from the market potential of their inventions. Hence, innovativeness might spur entry and not impede it.

2.1.2.2. Number of competitors in a market: A model with fixed costs

There is an interesting literature on the determinants of the number of firms active in an industry. Sutton (1991, 1998, 2007) develops a theory of a lower bound of concentration. He considers exogenous and endogenous barriers to entry. If entry barriers are largely exogenously given, the minimum value of concentration tends to zero as market size increases. However, if fixed costs are endogenously determined by advertising and/or research and development, Sutton predicts that the minimum equilibrium value of concentration is bounded from below. The equilibrium value of the number of firms is among other things determined by the toughness of competition, with a Bertrand oligopoly as the toughest market structure.

Bresnahan and Reiss (1991), Berry and Reiss (2007) discuss and estimate entry into small markets. They identify entry thresholds and ratios of entry thresholds revealing the nature of competition and the relevance of fixed costs. A recent empirical study on the relation between market size and the size distribution of firms is Campbell and Hopehayn (2005).

We consider a representative firm i which competes with $n-1$ other producers in a Cournot oligopoly[4]. In addition to constant marginal costs c, every firm has to cover fixed costs F. The assumption that all fixed costs are sunk is used for simplicity. Any sunk costs larger than zero would produce results similar to the ones presented below. If fixed costs are not sunk an entrant would not take them into account, as they can be recovered after leaving the industry. However, in practice, a part of capital will always be sunk.

[4] Bresnahan and Reiss (1990, 1991) and Berry (1992) discuss the relation between market size and the number of firms. Clearly, Sutton (1991, 1998) is also highly relevant if this question is considered. Cf. also the surveys by Berry and Reiss (2007) and Sutton (2007).

The inverse demand function is defined in the following (standard) way:

$$p_i = a - bq_i - b(n-1)q_j, \tag{2.1}$$

where the price demanded by firm i (p_i) depends on the reservation price a, the output level of firm i (q_i) and the individual outputs of all other competitor firms j (q_j) which are supposed to be identical. All outputs are characterized by the same price elasticity b.

This assumption leads to a simple profit function:

$$\pi_i = (a - bq_i - b(n-1)q_j)q_i - cq_i - F. \tag{2.2}$$

Optimizing this function with respect to output q_i, assuming homogenous firms with identical output levels and solving for q (the identical individual output of all firms in the market), leads to:

$$q = \frac{p-c}{b} = \frac{a - bnq - c}{b} = \frac{a-c}{b(n+1)}. \tag{2.3}$$

Equation (2.3) shows that the optimal output level q of every competitor depends negatively on the marginal costs c and on the number of firms n active in the market.

Since a general assumption is that entry occurs until all profit is dissipated, we determine the optimal number of firms in a market by solving the zero profit condition. As firms' sales (s) are identical, they can be defined as the average industry sales (S/n) determined by the optimal output level q derived in Equation (2.3).

$$\frac{S}{n} - cq - F = \frac{S}{n} - c\frac{a-c}{b(n+1)} - F = 0. \tag{2.4}$$

Solving for n, leads to the following expression:

$$n = \frac{Sb - ac + c^2 - bF + \left((Sb - ac + c^2 - bF)^2 + 4b^2FS\right)^{\frac{1}{2}}}{2bF}. \tag{2.5}$$

The industry sales volume S is simply defined as $S = pnq$. Exchanging p with the inverse demand function defined in Equation (2.1), and then replacing q by the optimal output determined in Equation (2.3) leads to:

$$S = pnq = \frac{(a+nc)n(a-c)}{b(n+1)^2}. \tag{2.6}$$

This relation is inserted into equation Equation (2.5). Solving for n leads to an explicit expression for the optimal number of firms in a market (n):

$$n = -1 + \frac{a-c}{\sqrt{bF}}. \tag{2.7}$$

This relation implies that the maximal number of firms falls with larger fixed costs F as well as with higher marginal costs c, and rises with reservation price a. More interesting, however, is the average firm size (S/n), as the costs have opposing effects: On the one hand, in the absence of entry barriers, higher marginal costs c lead to a lower output level (see Equation 2.3). On the other hand, fixed as well as marginal costs restrict the number of firms (see Equation 2.7), and therefore, increase the market shares ((S/n)) of the existing firms. Hence, both the nominator and the denominator of n/S are affected by the cost conditions and it remains unclear which effect dominates. The number of firms in an industry is determined by the following condition:

$$\frac{n}{S} = \frac{b}{bF + c(bF)^{\frac{1}{2}}}. \tag{2.8}$$

The number of firms in an industry is negatively affected by fixed costs F as well as by marginal costs c. This implies in turn that average firm size (S/n) is positively affected by both F and c. Given that output is reduced if marginal costs c rise (see equation 2.3), this result is not self-evident. Surprisingly, the constant term of the demand curve, a, has no effect on the maximal number of firms.

The model is based on the assumption that entry occurs until profits are dissipated. In such a scenario, by construction a connection between fixed costs and profitability cannot exist as profits are always zero. However, this is clearly the result of ignoring the integer constraint on the number of competitors n. If the integer condition is taken into account, raising fixed costs can lead to higher profits as the size of the market may not be large enough to allow entry of an additional firm. Consequently, the incumbents earn positive profits, as illustrated in the following equation in which the market size is n_0 firms.

$$\frac{S}{n_0} - cq_{n_0} - F > 0 \geq \frac{S}{n_0+1} - cq_{n_0+1} - F. \tag{2.9}$$

As an example, assume $a - c = 2$ and $b = F = 1$, which results in $n = 1$ and $\pi_i = 0$. If fixed costs are now slightly reduced to 0.9, the new n connected with zero profits is 1.108. As this is not an integer, with $n = 1$ the incumbent realizes profits of 0.1. If entry occurs and $n = 2$, profits become negative. Hence, in this situation the incumbent takes profits and entry will not occur despite the fact that the entrant faces exactly the same cost conditions as the incumbents, and therefore, in the view of Stigler (1968), entry barriers do not exist.

This opportunity for positive profits will be larger, the higher the fixed costs F are. Comparing the firm profit levels in a market with n_0 incumbents without (π_{n_0}) and with entry (π_{n_0+1}) leads to:

$$\pi_{n_0} - \pi_{n_0+1} = \frac{(a+n_0c)(a-c)}{(n_0+1)^2 b} - \frac{c(a-c)}{b(n_0+1)} - \frac{\big(a+(n_0+1)c\big)(a-c)}{(n_0+2)^2 b} + \frac{c(a-c)}{b(n_0+2)}.$$

The derivative of this profit difference with respect to n_0 is, as expected, negative. Hence, the profit reduction induced by entry is decreasing in the number of firms. Evidently, the maximal number of firms n, which is compatible with non-negative profits, is decreasing in fixed costs F, and therefore, the potential for realizing profits without attracting entry is increasing in F. The maximal number of firms is also decreasing in marginal costs c.

2.1.3. Empirical testing and data

In accordance with the theoretical considerations, we estimate two models: The first model analyzes the effect of entry threat on firms' price setting behavior and consequently on profitability. Thus, this model tests the theoretical result that the threat of entry has a disciplinary effect on incumbents' behavior. Previous empirical evidence usually uses the actual number of entries to approximate the threat of entry which is not a good approximation according to Martin (2002). In the second part, we test our theoretical model derived in Section 2.1.2.2. Hence, we show whether the number of firms in a market responds to barriers to entry, which we reflect by inserting fixed costs.

In order to test these conjectures, we use firm level information from the Mannheim Innovation Panel (MIP). Data collection is carried out by the Centre for European Economic Research (ZEW) on behalf of the Federal Ministry of Education and Research. The MIP provides annual information on innovative behavior in the German manufacturing sectors between 1992 and 2005[5].

2.1.3.1. Threat of entry, barriers to entry and firm's profitability

A number of empirical studies on barriers to entry already exists. They usually investigate the determinants of and/or impediments to market entry (and exit). Some also investigate the profitability effects. With respect to the latter relation, Amel and Liang (1997) find that new entrants in banking markets are attracted by high profits, market size and growth, and that entry reduces market power in pricing. The studies on the determinants of entry barriers address the question of natural or strategic barriers like scale economies, excess capacity, limit pricing, product differentiation by means of advertising or innovative activity. Furthermore, the benefits of entry into a particular market are regarded by taking account of expected profitability and market growth[6]. A recent example is Berger et al. (2004). The empirical evidence is quite supportive and unambiguous concerning profitability and market growth, but, in the summarizing view of Siegfried and Evans (1994), is much less convincing with respect to the other determinants like scale economies, excess capacity, limit pricing and product differentiation.

The effect of the threat of entry on pricing behavior, and therefore, also on profitability of firms is much less frequently investigated, although it has a strong rooting in theory.

[5] More information about the MIP can be found in Appendix A.1.

[6] One could argue that the subjective assessment could also be based on the objectively observed frequent entry of challengers into a market. However, this assertion is rejected by our empirical results. See below.

Harrod (1952) already suggests that if entry is easy, the incumbents will set prices close to average costs. This perception of the working of markets is also at the center of the theory of Baumol et al. (1982). We intend to estimate the impact of perceived threat of entry on the profitability of companies. This perceived threat of entry is expected to determine the pricing behavior of firms. Firms which are producing in easy-to-enter industries should be disciplined by this potential competition, even if entry does not occur in practice. Perhaps some firms will decide to optimize by maximizing short-run profits, and accept that in the long run entry will take place and profits will erode. This is basically Gaskins' (1971) argument.

Our empirical study investigates the determinants of profitability. The dependent variable is the profit margin. This variable is sometimes called excess return on sales and expresses the following:

$$\frac{\pi_i}{s_i} = \frac{s_i - labor\ cost_i - capital\ cost_i - material\ cost_i}{s_i},$$

with π_i denoting profits and s_i being firm (not industry) sales. If firms are in the long-run equilibrium and are operating within the range of their production functions with constant returns to scale, the excess profit return on sales will, on average across all products produced by the firm, equal the Lerner index. With constant returns to scale marginal costs (c) are equal to average costs (AC). One can therefore write:

$$\frac{\pi}{s} = \frac{pq - ACq}{pq} = \frac{p - c}{p},$$

with p being the price set by the firm and q the quantity produced by the firm (i). Hence, our measure is the price-cost margin, where the capital costs have been subtracted and need not be taken into account by capital divided by sales as an explanatory variable as in other empirical models considering the price cost margin. The usual way to estimate price-cost margins was introduced by Collins and Preston (1969). There are numerous studies that follow the same methodology.

In the given context, the most important variable is the *threat of entry*. We use the threat and not the actually occurring entry rates as explanatory variable because our main hypothesis is that the firms take action themselves to deter entry by reducing prices if entry is a definite possibility. Hence, the subjective assessment of the entry conditions is decisive, in our view, to explain profitability.

Hypothesis 1: *Threat of entry disciplines incumbents' behavior regarding its price setting power, and hence, firms' profitability.*

This seems to be one of the few cases where the use of subjective data is totally appropriate. The subjective perception of the managers concerning potential entry determines their pricing decisions and the resulting profitability. As stated above, the subjective assessment may be the result of observing that entry actually takes place, in which case there would be no difference between the objective situation and the subjective evaluation. The variable concerning entry is based on the following question: "Please indicate, in how far the following criteria describe the competitive situation in your main market: High threat to your firm's market position by entry of new competitors". The evaluations are rated on a four point Likert scale ranging from "fully applies" to "does not apply at all". We use a dummy variable, which assumes unit value if a firm ticks the box "fully applies".

Obviously, any study analyzing profitability has to carefully take into account the competitive situation in general. In our case, we do this in two different ways. First, we use information concerning the relevant market supplied by the firms themselves. They were asked to evaluate how many main competitors they have. The options proposed for their assessments were "none", "1 to 5", "6 to 15" and "more than 15". We compute a dummy variable called *intermediate competition*, which has unit value if the firm chooses the option "6 to 15" and secondly, a dummy variable called *intensive competition* if the firm chooses the option "more than 15". We suppose that the evaluation of the situation by the firm itself offers a more accurate representation of competitive pressure than conventional concentration indices (see Section 2.2 for a test on the appropriateness of standard concentration measures to represent competition in the relevant market).

Next, we take account of the size structure of the competitors. We use a dummy variable called *competitors size*, which has unit value, if a firm expresses that the competitors are predominantly larger than the firm itself. We have also information on the importance of price competition. Firms were asked to rank the importance of several characteristics of their competitive environment (product quality, technical advancement, service, product variety, advertising and price). If the option "price" was given the highest priority, we create a dummy variable with unit value. This variable

Table 2.1.: Variables description for estimation of profitability on threat of entry and barriers to entry

Variable name	Type	Description
Dependent variable		
return on sales	categorical	profit generated by unit of sales (see Table 2.3)
Explanatory variables		
threat of entry	indicator	market position highly threatened by entry
intermediate competition	indicator	6 to 15 main competitors
intensive competition	indicator	more than 15 main competitors
competitors size	indicator	competitors predominantly larger
strong price competition	indicator	price is most important characteristic of competitive environment
demand growth [a]	continuous	growth of 3-digit industry sales
market share	continuous	fraction of firm sales per industry sales (3-digit)
export	continuous	export intensity
import	continuous	imports per sum of imports and domestic production (2-digit)
capital intensity	continuous	capital fixed and working per employee
log(employees)	continuous	logarithm of number of employees
East Germany	indicator	firm location in East Germany
industry dummies	indicators	10 industry dummies (see Table A.1 in the Appendix)
time dummies	indicators	year 2002, year 2003, year 2004

[a] lagged values.

is called *strong price competition.* Another important impact factor for profitability linked to consumers is the market potential, which is often reflected by the lagged market *demand growth* proxied by the growth of sales at the three-digit industry level.

Hypothesis 2: *Firms' perception of their competitive situation influences their price setting behavior, e.g. high competitive pressure (reflected by intensive competition, price* *competition, competitors size) causes firms to set lower prices, and consequently, their profitability decreases.*

More conventional control variables are the *market share* measured as the fraction of firm sales to 3-digit industry sales, the firm's share of sales due to *export* and industry imports divided by the sum of industry imports and industry production at 2-digit level (*import*) and the *capital intensity* (capital fixed and working per number of employees). Clearly, all four variables are also used to represent the competitive environment of a firm and the industry. Profitability may also depend on firm size which is approximated by the number of *employees*. *East Germany* is a dummy variable, which indicates that the firm is situated in the Eastern part of Germany (the former GDR). Finally, we add *industry* and *time dummies*, because other specific circumstances in an industry and/or cyclical factors, which perhaps are not reflected by our other variables, may affect the returns.

The variables included in the estimation of the firm profitability are summarized in Table 2.1.

2.1.3.2. Barriers to entry and number of competitors in a market

As already described deriving the model in Section 2.1.2.2, it is of utmost importance to identify n/S and not just n, as the number of active firms will usually but not necessarily rise with market size. In order to assess the size of the relevant market, we restrict our sample to those firms which indicate that their rivals are of similar size, hence, homogenous firms. This procedure implies that our dependent variable is $n/(n * s_i) = 1/s_i$, i.e. the inverse of individual firm sales. This variable is, thus, directly comparable to the dependent variable "establishments' sales" used by Campbell and Hopehayn (2005).

As derived in the model in Section 2.1.2.2, the number of firms, which can survive in a market, is obviously also determined by cost conditions. Both fixed and marginal costs are expected to reduce the number of firms. These costs are approximated by *capital intensity*, reflecting the extent of fixed costs, and the average *salaries and wages* per employee including the firms' contributions to social security, representing marginal costs.

Hypothesis 3: *The number of firms in a market is limited by the extent of entry barriers approximated by fixed costs.*

One possible strategy to avoid entry could be to reduce prices to such an extent that entry is no longer profitable. If this were true, we would not observe a statistical association between the threat of entry and the number of competitors. The absence of entry barriers does not necessarily imply a larger number of active competitors if incumbents act strategically.

Hypothesis 4: *The reduction in profits is sufficient to make entry unattractive.*

It cannot be excluded that we may encounter endogeneity problems. Schmalensee (1989) argues that cross sectional studies are prone to simultaneity problems and our approach might not be free of such feed back relations. However, it is impossible to find reliable instrumental variables. On the other hand, it seems to be quite unlikely that endogeneity is responsible for our main results.

As described above, Sutton (1991, 1998, 2007) emphasizes the role of toughness of price competition on the number of competitors. If competitive pressure is strong, as in the case of Bertrand behavior, fewer firms are supported in equilibrium, as a greater increase in market size is required for an additional profitable entry to take place. This hypothesis is tested by our variable *strong price competition*, defined similarly as in the last section.

Sutton also points to a non-linear relation between the number of firms and industry size, as output per firm is expected to rise with total *industry sales*. However, a test on this hypothesis is not trivial in our case. We have no exact information on the number of firms active in an industry, but instead use the responses to our alternative categories. These answers are now used to approximate the number of firms in the following way: If a firm indicates that it has 1 to 5 main competitors, we compute the total number by adding to the average number of 3 competitors the interviewed firm itself, which results in a total of 4 firms active in the respective industry. If a firm states that it has 6-15 main competitors, our estimate of the industry structure amounts to a total of 11 companies. Finally, if a firm chooses to tick the option “more than 15 competitors”, we take 20 as a rough “guesstimate” of the total number of active firms. These figures are multiplied by the sales of the responding firm[7]. Clearly, this procedure is somewhat arbitrary, but we see no alternative method to test for a possible non-linear relation between market size and the number of firms.

Table 2.2.: Variables description for estimation of the role of barriers to entry on the number of competitors

Variable name	Type	Description
Dependent variable		
number of firms	continuous	number of firms per market sales for homogenous firms, reflected by the inverse sales of the individual firm
Explanatory variables		
threat of entry	indicator	market position highly threatened by entry
strong price competition	indicator	price is most important characteristic of competitive environment
industry sales	continuous	approximated number of homogenous competitors: average number of competitors times firm sales (in mio. €)
capital intensity	continuous	capital fixed and working per employee (proxy for fixed/sunk costs)
salaries and wages	continuous	logarithm of expenditures for salaries and wages per employee (proxy for marginal costs)
East Germany	indicator	firm location in East Germany
industry dummies	indicators	10 industry dummies (see Table A.1 in the Appendix)
time dummies	indicators	year 2002, year 2003, year 2004

As before, we add nine *industry dummies*, to control for specific circumstances characterizing a market and three *year dummies* to reflect cyclical impacts. The dummy variable *East Germany* is included, as the firms in the new Bundesländer (the former GDR) are on average younger and smaller than their Western counterparts.

[7] Remember that we assume homogenous firms, and only keep those observations for which "competitors are predominantly of equal size" is indicated.

The variables included in the estimation of the number of firms are summarized in Table 2.2.

2.1.3.3. Data and descriptive statistics

As stated in Section 2.1.3.1, our measure of profitability is the variable return on sales which is measured in categories as depicted in Table 2.3.

Table 2.3.: Measured categories of return on sales

RoS[1]	Class	RoS[1]	Class	RoS[1]	Class
< 0 %	0	(4 - 7 %]	3	> 15 %	6
(0 2 %]	1	(7 - 10 %]	4	don't know	7
(2 4 %]	2	(10 - 15 %]	5		

[1] RoS: Return on sales

This variable was included in the 2003 and 2005 MIP surveys. The information is available for the years 2001 to 2004 because in both surveys firms were asked to state the return on sales for the two years preceding the survey year. Information on exports, the number of employees, sales and capital intensity has been taken from the respective waves. The variables threat of entry and competition were only included in the year 2005 and represent the competitive situation in 2004. We conjecture that neither the threat of entry, nor competition change much in the short-run. Therefore, we hold these variables constant over time for the observation period of 2001 to 2004.

As concerns the industry-level information incorporated in the market demand, we combine information gathered in the biennially published report of the German Monopolies Commission which provides industry sales at the three-digit NACE level. Industry sales are used to compute each firm's market share and sales growth rates which proxy the demand growth, and hence the market potential. Information on imports and domestic production are included in two-digit NACE level and are taken from OECD data.

As can be seen in the descriptive statistics depicted in Table 2.4, the average firm generates between 2 % and 7 % of return on sales as the mean represents the average category number (see Table 2.3 for the assignment of return on sales category and actual return on sales). Regarding the variable for testing our main hypothesis, that threat of entry causes the firms to reduce their prices, accepting a reduction of return on sales in order to deter entry, we find that about 14 % of the firms think that the market in which they mainly operate is characterized by potential market entry.

Table 2.4.: Descriptive statistics for profitability and number of firms

Variable name	Mean	Std.Dev.	Min	Max
Dependent variable: Profitability				
return on sales	2.341	1.718	0	6
Explanatory variables				
threat of entry	0.136	0.343	0	1
intensive competition	0.135	0.342	0	1
intermediate competition	0.240	0.427	0	1
competitors size	0.361	0.480	0	1
strong price competition	0.490	0.500	0	1
demand growth	0.007	0.084	-0.624	0.885
market share	0.007	0.084	-0.624	0.885
export	0.232	0.249	0.000	0.919
import	0.251	0.133	0.060	0.712
capital intensity	0.097	0.150	0.000	1.956
log(employees)	4.379	1.482	1.609	8.545
East Germany	0.349	0.477	0	1
Number of observations		3,626		
Dependent variable: Number of firms				
inverse sales	0.295	0.480	0.000	5.113
Explanatory variables				
threat of entry	0.131	0.338	0	1
strong price competition	0.512	0.338	0	1
industry sales	0.175	0.386	0.001	3.733
capital intensity	0.115	0.312	0.000	3.613
salaries and wages	36.691	15.641	5	100
East Germany	0.410	0.492	0	1
Number of observations		2,343		

Firm's profitability does not only depend on the *threat of entry* but also on some other factors that are included as control variables, like competition, market situation, exports, imports and firm size. Over 13 % of the firms are exposed to intensive competition, in that they face more than 15 competitors, and almost a third of the firms experience intermediate competition and compete with 6 to 15 firms. Furthermore, more than 36 % of the firms face competitors that are larger than themselves (*competitors size*). Profitability as well as the need to react to potential entry also depends on the market potential, which is often reflected by the lagged market demand growth. The average firm faces a market demand growth of 0.7 % per year.

2.1.4. Estimation results

This section presents, first, the empirical results for the test of entry threat on profitability, and second, the results of the investigation of the optimal number of firms in a market.

In order to test the effects of potential entry on profitability we estimate an ordered probit for *return on sales* which is measured categorically as described in Table 2.3. As usual, in the context of discrete choice, the model is based on a latent variable y^* (here: profitability) being explained in a linear manner by $x\beta$. Since the latent variable is unobserved, we rely on its surveyed categorical values. The econometric model can be written as,

$$y_i^* = x\beta + \epsilon_i \; with \; i = 1, \dots, N$$

$$y = \begin{cases} 0 \quad if & y_i^* \leq \mu_0 \\ 1 \quad if & \mu_0 < y_i^* \leq \mu_1 \\ \vdots & \\ 6 \quad if & y_i^* > \mu_5 \end{cases}$$

As opposed to the usual ordered probit model, the cut-off points μ_k are known (see Table 2.3). Thus, the thresholds need not be estimated. Furthermore, by using the true threshold values we are able to identify the variance and to interpret the estimated

Table 2.5.: Results for the link of profitability, threat of and barriers to entry using homo- and heteroscedastic ordered probits with known thresholds

	Homosc.	**Heterosc.**	**Homosc.**	**Heterosc.**
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
threat of entry	-0.006** (0.003)	-0.007*** (0.003)	-0.005* (0.003)	-0.005** (0.003)
intensive competition	-0.010*** (0.003)	-0.011*** (0.003)	-0.008*** (0.003)	-0.009*** (0.003)
intermediate competition	-0.009*** (0.002)	-0.009*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
competitors size	-0.005*** (0.002)	-0.005** (0.002)	-0.006*** (0.002)	-0.005*** (0.002)
strong price competition			-0.012*** (0.002)	-0.012*** (0.002)
demand growth	0.045*** (0.012)	0.045*** (0.011)	0.042*** (0.011)	0.041*** (0.011)
export	0.016*** (0.004)	0.016*** (0.004)	0.014*** (0.004)	0.014*** (0.004)
import	0.001 (0.010)	-0.002 (0.010)	-0.003 (0.010)	-0.006 (0.010)
capital intensity	0.013** (0.006)	0.015** (0.006)	0.014** (0.006)	0.016*** (0.006)
log(employees)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
East Germany	-0.002 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.000 (0.002)
constant	0.030*** (0.007)	0.029*** (0.007)	0.038*** (0.007)	0.036*** (0.007)
industry dummies	included	included	included	included
time dummies	included	included	included	included
$\hat{\sigma}$	0.051*** (0.001)	0.052*** (0.003)	0.051*** (0.001)	0.053*** (0.003)
LR(heteroscedasticity) [a]		80.71***		74.21***
χ^2(heteroscedasticity) [b]		80.33***		73.35***
log Likelihood	-6,855.02	-6,817.92	-6,834.88	-6,794.53
χ^2 *(all)* [c]	157.66***	166.91***	199.10***	216.09***
χ^2 *(industries)* [d]	43.36***	89.06***	41.98***	92.49***
χ^2 *(time)* [d]	0.63	2.72	0.58	1.99
McFadden's R^2	0.011	0.012	0.014	0.016
McFadden's adjusted R^2	0.008	0.006	0.011	0.010
Cragg-Uhler's R^2	0.043	0.046	0.055	0.059
BIC	-15,811.54	-15,745.61	-15,843.61	-15,793.19
Number of observations	3,626	3,626	3,626	3,650

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of an ordered probit with known thresholds, i.e. the cutoff points need not to be estimated. Consequently, the coefficients are interpretable as marginal effects like in the linear model. Standard errors are clustered by firm.

[a] LR(heteroscedasticity) is a LR-test with 1 degree of freedom.

[b] χ^2(heteroscedasticity) displays the test of joint significance of the variables determining heteroscedasticity.

[c] χ^2(all) displays a test of the joint significance of all variables.

[d] χ^2(industries) and χ^2(time) display a test on the joint significance of industry and time dummies. For definition of industry dummies see Table A.1 on page 210 in the Appendix.

coefficients as in a linear regression model, i.e. as marginal effects of the latent model (see Czarnitzki, Kraft (2004a,b) and Verbeek (2000) pp. 192-195 for an example).

Since heteroscedasticity will lead to inconsistent estimates we account for groupwise multiplicative heteroscedasticity of the form $\sigma_i = \sigma exp(z_i \alpha)$ where z is a vector of variables suspected to cause heteroscedasticity. If heteroscedasticity is an issue in the ordered probit, α are additional coefficients to be estimated. In order to test if heteroscedasticity is an issue in our estimation, we perform LR (likelihood ratio) tests. Heteroscedasticity is modeled by the industry and time dummies, by the East Germany dummy and by firm size dummies. The LR tests show that the assumption of homoscedasticity has to be rejected.

Table 2.5 displays the results of the ordered probit with known cut-off points. Our hypothesis that the threat of entry reduces profitability is confirmed. The results show a negative significant effect of threat of entry on return on sales, and hence, a disciplining effect with respect to setting above normal prices. Regarding the control variables, return on sales seems to be sensitive to market conditions. Profitability depends negatively on competition, either intensive or intermediate, and is negatively influenced by the size of competitors. Price competition has also a negative impact on profitability. This reflects the mechanism that a stronger competition forces the firms to lower prices, and hence, to accept a reduction in return on sales. Notice, that the threat of entry has an independent effect aside of the number of competitors. Similarly, the threat of entry has an independent and additional impact if the variable price competition is included. This is not self-evident, as we hypothesize that the threat of entry leads to price reductions, and therefore, a high correlation is probable. Furthermore, firms' profitability is strengthened if other proxy variables reflecting barriers to entry exist which confirms that barriers to entry, particularly sunk costs, allow firms to exert their market power and to set higher prices, i.e. to increase profitability. We measure barriers to entry by firm's capital intensity and find a positive effect on profitability which confirms that barriers to entry increase the price setting power of firms. Moreover, the market potential is a crucial factor for firm profitability; demand growth has a significant positive effect on return on sales. And finally, exports generate higher return on sales.

Our test of the impact of entry barriers on the number of competitors in a market derived in the model in Section 2.1.2.2 is based on ordinary least squares (OLS) regressions with clustered standard errors. Estimation results are presented in Table 2.6.

Table 2.6.: OLS regression results for the number of competitors with respect to entry barriers

	Coeff. (Std.Err.)	Coeff. (Std.Err.)	Coeff. (Std.Err.)
threat of entry	0.043 (0.052)	0.057 (0.052)	0.060 (0.051)
strong price competition		-0.087*** (0.030)	-0.082*** (0.030)
industry sales			-0.156*** (0.026)
capital intensity	-0.106*** (0.022)	-0.103*** (0.022)	-0.083*** (0.023)
salaries and wages	-0.381*** (0.053)	-0.381*** (0.052)	-0.347*** (0.053)
East Germany	0.042 (0.035)	0.053 (0.034)	0.049 (0.034)
constant	1.704*** (0.202)	1.744*** (0.204)	1.642*** (0.202)
industry dummies	included	included	included
time dummies	included	included	included
log Likelihood	-1,345.10	-1,333.77	-1,313.32
F(all) [a]	8.93***	8.81***	11.18***
F(industries) [b]	7.71***	7.92***	6.73***
F(time) [b]	0.11	0.11	0.18
R^2	0.203	0.211	0.224
Adjusted R^2	0.199	0.205	0.218
BIC	-15,357.67	-15,372.56	-15,405.71
Number of observations	2,343	2,343	2,343

***(**,*) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of OLS regressions. Standard errors are clustered by firm.
[a] F(all) displays an F-test of the joint significance of all variables.
[b] F(industries) and F(time) display F-tests on the joint significance of industry and time dummies. For the definition of industry dummies see Table A.1 on page 210 in the Appendix.

It turns out that the threat of entry is not associated with a significantly higher number of competitors. Hence, the threat alone is sufficient to induce the incumbents to cut prices to such an extent that entry is no longer profitable. As shown in the section on profitability, taking into account the independent effect of the number of competitors, the threat of entry implies significantly reduced profits and this reduction in profitability seems to be sufficient to avoid any occurrence of entry. The insignificance of the coefficient of entry threat is very robust and does also not alter if, for instance, the variables considered in the profitability equation are additionally included. This outcome of our empirical study also offers evidence against the possibility that the firms base their assessment of the existence of entry barriers on the mere observation that entry actually occurs.

Our cost variables – capital intensity for sunk costs and salaries and wages for marginal costs – have the expected effects and are both significant confirming our hypothesis that barriers to entry influence the number of competitors negatively. We find evidence for a non-linear relation between industry size and the number of companies. Furthermore, we find a strong impact of price competition on the total number of competitors which supports our conjecture that Bertrand competition leads to a smaller number of firms in a market.

2.1.5. Concluding remarks

This section reports the results of a study which employs rarely available variables. We investigate the effects of the perceived threat of entry on profitability and the number of competitors. The entry threat leads to lower profits, and the reduction in profits is sufficient to make entry unattractive, as our variable entry threat is actually not associated with a higher number of firms.

While subjective data is usually criticized for its limited reliability, we think it is quite useful in the present context. The subjective assessment of managers concerning the characteristics of the markets, in which their firms operate, will determine firm behavior. Obviously, the view of the managers may eventually later turn out to have been wrong, but nevertheless the individual evaluation serves as the basis of their decisions.

The observed market structure and market performance are among other things determined by strategic decisions of firms. This section aims to identify one reason for strategic behavior of firms and the consequences thereof. Clearly, there is much scope left for additional research on the decisions of firm managers in situations of imperfect competition, but it is very difficult to observe not only the outcome but also the reasons for market conduct.

It is obvious that much of the analysis could be improved by the use of panel data. Before-after comparisons would help to solve or attenuate the diverse endogeneity and causality issues, which can hardly be totally avoided in the case of cross-sectional data.

However, we make use of very specific variables and we are glad to have them at all, and a panel is probably too much to ask for at the present time.

2.2. Standard concentration indices: Good indicators for market structure?

2.2.1. Motivation

In most Western countries, antitrust agencies rely their decisions, e.g. in merger cases, on market concentration indices calculated on the basis of clearly defined product and geographic markets. This method suggests that a causal relationship between market concentration and firm profits exist. Most economic models predict a positive relation between market concentration and profitability. However, in empirical research, this positive link is frequently either only weak, or cannot be estimated, or the relation even turns out to be negative. Schmalensee (1989) concludes: "The relation, if any, between seller concentration and profitability is weak statistically, and the estimated concentration effect is usually small. The estimated relation is unstable over time and space and vanishes in many multivariate studies."

Recent IO literature has abandoned the empirical approach to link profitability to market concentration. Slade (2004) discusses the shortcomings in detail. One reason is the inability of empiricists to determine causality instead of correlation. Particularly in cross-section analyses, endogeneity problems arise when relating concentration measures to profitability. Evans et al. (1993) find two reasons: First, feedback effects of performance into market structure may exist, e.g. via investment in new capacity, R&D, entry and exit. Feedback effects are also the basis for the efficiency argument of Demsetz (1973) and Peltzman (1977). They argue that some firms may produce more efficiently than others. Consequently, they grow in terms of size and market share, and this leads to more concentrated markets. Second, Evans et al. (1993) postulate that concentration is a function of outputs and prices which are endogenous.

Slade (2004) lists more shortcomings: Industry classifications, which are assumed to be the best approximation for the "market", are based on a too broad definition. Consequently, industries may pool "sub-markets" with very different structures. Furthermore, firms are assigned to one industry, their perceived "main industry", but operate in several different industries. The basic structure-conduct-performance (SCP) paradigm has also been criticized because it is supposedly not derived from models with optimizing agents.

Another shortcoming of conventional concentration indices is that they are unable to reflect the toughness of competition. Sutton (1991, 1998, 2007) shows that the equilibrium number of firms in a market is – among other factors – determined by the toughness of competition, with a Bertrand oligopoly as the toughest market structure. If for some reason the toughness of competition increases, industry-level concentration indices will display higher values, although in this situation the competitive pressure has become stronger. The price cost margin does not have this problem. As shown below, we are able to consider toughness of competition in a market.

However, in her own empirical study Slade (2004) finds strong support for the old-fashioned SCP paradigm. She investigates the non-ferrous-metal industries since products are assumed to be homogenous, and incorporates both the traditional SCP paradigm and the market share model based on Demsetz (1973). In contrast to the established approach, Slade (2004) calculates firm-specific Herfindahl indices: She accounts for all markets in which a firm is active and calculates the average Herfindahl index weighted by the firm's output share in the individual commodity market.

Delorme et al. (2002) account for feedback effects between all three components of the SCP paradigm and confirm the paradigm at least partly. They estimate a simultaneous equations approach including a specific lag structure and find that profitability depends on concentration, but they cannot confirm the reciprocal effect.

In this study, we use alternative measures of market structure and scrutinize the appropriateness of standard industry-based concentration indices estimating profitability equations for a number of German manufacturing firms. We use conventional industry-based concentration indices, the individual market share (relating firm sales to industry sales) and, in addition, firm-level questionnaire data about the perceived market environment. The latter includes the number of competitors in a firm's main market, the average size of the competitors, the intensity of price competition and buyer power. The variables describing the competitive situation are used along with other variables to explain profitability.

The results based on the industry classification display no effect on profitability. However, direct information concerning the competitive environment works extremely well in explaining profitability. Apparently, the firms themselves assess the competitive environment much more accurately than the conventional and broadly-used concentration measures based on industry classification. Unlike the firms' assessment, the aggregate variables are not able to identify the relevant market of the companies. Problems with the published figures may arise because of the frequently too strong aggregation. Furthermore, the attribution of firms to specific industries is not trivial if firms are active in several sectors. Moreover, the relevant market is rarely exactly identical to the national one. Many companies produce in or export to many other countries, or are just in one region present. In such cases, the concentration ratios measured on the national level do not capture the relevant market.

The profitability measure we use throughout this section is return on sales, which is equivalent to the price cost margin, where the capital costs are subtracted. Arguing in line with the traditional SCP framework, our measure reflects firm performance and enables us to draw conclusions concerning firms' conduct, e.g. concerning their price setting behavior. Many authors, however, use the price-cost margin itself as a measure of competition . The main advantage is the identification of the relevant market. Aside from market power, price cost margins also reflect efficiency advantages (see Boone et al. (2007) on this issue) since they are also determined by costs. Consequently, a high value of price-cost margins is not inevitably the result of low competitive pressure. Our empirical evidence, however, supports the use of price-cost margins as a competition measure since it is strongly related to competitive pressure as assessed by the managers themselves.

2.2.2. General considerations and research strategy

Most oligopoly models like Cournot or Bertrand predict a negative relation between the number of firms active in an industry and profitability, for homogenous and heterogeneous products. If firms active in an industry form a cartel, this hypothesis does not hold, since monopoly profits are generated although the number of firms exceeds one. But, in such a setting, incentives exist to secretly break the agreement or to form an independent fringe (Selten (1973), D'Aspremont et al. (1983), Martin (2002) Chapter 10). These incentives become more relevant with an increasing number of colluding firms. Consequently, even in industries with cartels, a negative relation between profitability and the number of firms probably exists.

In contrast to this view, it is also hypothesized that the positive association between profitability and concentration is due to efficiency advantages of large firms. If a firm is more efficient than others, it will be able to reduce prices and will gain market share at the expense of the less efficient producers. As a result, concentration indices should be positively correlated with profitability of the larger firms, but not because of collusion.

The predictions from theory have been tested in numerous studies. Usually, concentration measures constructed on a more or less disaggregated industry-level are applied to explain profitability measures. In order to check for possible efficiency differences, the individual market shares are also included. However, the results are mixed. In any case, the empirical relations found between concentration indices and profitability are not very robust.

In this section, we compare the appropriateness of different measures reflecting the competitive environment of firms. To do this, we use different data sources: First, publicly available, conventional measures of market concentration, and second, variables from the questionnaire-based survey displaying firms' assessment of their competitive situation. We suppose that, in general, a firm's own evaluation of the competitive situation is more accurate than conventional industry-level concentration indices. This is because the industry-level data based on NACE codes may not exactly capture the relevant market, whereas in survey data the firms answer according to their perceived market environment, and "accurate market definition is extremely important for assessing models of firm profitability" (Slade (2004), p. 291).

The publicly available variables are the *C3* and *C6* concentration indices[8], the *Herfindahl* concentration index and industry sales. We use the latter to construct the firms' *market shares* by relating the individual sales to industry sales. These industry-level competition variables are gathered using information published in the biennial reports of the German Monopolies Commission, which provides the relevant information at the three-digit NACE level. The years in between are linearly interpolated. It is possible that more disaggregated data would be more suited to describe the relevant market. However, quite a number of studies which investigate the effects of market structure rely on three-digit industry data, so a comparison with our survey-based variables seems to be appropriate and meaningful.

For our comparison between industry-based and survey-based data, we use firm level information from the Mannheim Innovation Panel (MIP). Most variables included in

[8] The C3 (C6) concentration index indicates the fraction of industry sales generated by the three (six) largest firms.

the regressions have been described in more detail in Section 2.1.3. The descriptions are summarized in Table 2.7. A description of the MIP can found in Appendix A.1.

The dependent variable is *return on sales* defined as

$$\frac{\pi_i}{s_i} = \frac{s_i - labor\ cost_i - capital\ cost_i - material\ cost_i}{s_i}.$$

If firms are in long-run equilibrium and are operating in the range of their production functions with constant returns to scale, this measure is the price-cost margin, where the capital costs have been subtracted and need not to be taken into account as an explanatory variable (e.g. capital divided by sales) as in other empirical models considering the price-cost margin. As in Section 2.1, it is measured by the categorical variable return on sales. The respective categories are depicted in Table 2.3 on page 21. The information is available for the years 2001 to 2004 (For more detailed description of all the relevant MIP variables, please, refer to Section 2.1.3).

Our approach is to use information about the competitive situation reported by the firms surveyed in the MIP. We use the dummy variables *intermediate competition* and *intensive competition*. Over 13 % of the firms are exposed to intensive competition, i.e. they face more than 15 competitors. Almost a third of the firms experience intermediate competition, competing with 6 to 15 firms. Next, we take into account the size structure of the competitors. We use a dummy variable called *competitors size*, which has unit value, if a firm expresses that the competitors are predominantly larger. This is the case for more than 35 % of the firms. We also have information on the importance of price competition. Unit value expresses that firms are exposed to *strong price competition*, which is the case for almost half of the firms.

Aside from supplier conditions, profitability may also be affected by buyer power. If a firm only sells to a few buyers, it is possible that these buyers exert so-called buyer power, which leads to price cuts. The concentration of buyer power is considered in the questionnaire by means of a question asking what share of the firm's sales is due to the three most important buyers. The possible answers were "100 %", "50-99 %", "20-49 %" and "below 20 %". We use the dummy variables *strong buyer power* when the alternative "100 %" is chosen, *quite strong buyer power* if the buyer concentration ranges between "50 and 99 %". 1.7 % of the firms report that all sales were generated by their three most important customers (*strong buyer power*). More than a quarter

Table 2.7.: Variables description for the estimations regarding perceived competitive situation versus standard concentration indices

Variable name	Type	Description
Dependent variable		
return on sales	categorical	profit generated by unit sales (see Table 2.3)
Explanatory variables		
Herfindahl	index	Herfindahl-Hirschman index of market concentration
C3 concentration	index	fraction of industry sales generated by the three largest firms
C6 concentration	index	fraction of industry sales generated by the six largest firms
intermediate competition	indicator	6 to 15 main competitors
intensive competition	indicator	more than 15 main competitors
competitors size	indicator	competitors predominantly larger
strong price competition	indicator	price is most important characteristic of competitive environment
strong buyer power	indicator	100 % of sales due to three most important customers
quite strong buyer power	indicator	50 % to 99 % of sales due to three most important customers
demand growth	continuous	growth of 3-digit industry sales
market share	continuous	fraction of firm sales in the industry (3-digit)
export	continuous	export intensity
import	continuous	imports per sum of imports and domestic production (2-digit)
capital intensity	continuous	capital fixed and working per employee
log(employees)	continuous	logarithm of number of employees
East Germany	indicator	firm location in East Germany
industry dummies	indicators	10 industry dummies (see Table A.1 in the Appendix)
time dummies	indicators	year 2002, year 2003, year 2004

generated over 50 % of sales from their three most important buyers (quite strong buyer power). As in Section 2.1, the competition and buyer power variables were only included in the 2005 questionnaire and represent the competitive situation in 2004. We conjecture that neither competition nor buyer power changes much in the short-run. Therefore, we hold these variables constant over time for the observation period of 2001 to 2004.

Table 2.8.: Descriptive statistics regarding analysis of competitive situation and concentration

Variable	Mean	Std.Dev.	Min	Max
return on sales	2.351	1.723	0	6
Herfindahl [a]	0.031	0.042	0.003	0.251
C3 concentration [a]	0.192	0.137	0.058	0.845
C6 concentration [a]	0.271	0.166	0.084	0.953
intensive competition	0.131	0.338	0	1
intermediate competition	0.240	0.427	0	1
competitors size	0.355	0.479	0	1
strong price competition	0.487	0.500	0	1
strong buyer power	0.017	0.129	0	1
quite strong buyer power	0.257	0.437	0	1
demand growth [a]	0.000	0.074	-0.624	0.339
market share [a]	0.005	0.015	0	0.164
export	0.239	0.252	0	0.919
import	0.250	0.135	0.060	0.712
capital intensity	0.098	0.153	0.000	1.956
log(employees)	4.389	1.537	1.609	10.881
East Germany	0.341	0.474	0	1
Number of observations		3,008		

[a] Lagged values

Another important factor that impacts on profitability and is also linked to consumers is the market potential. Market potential is often reflected by the lagged market *demand growth*, proxied by the growth of sales at the three-digit industry level. The information is collected by using the Monopolies Commission data (see Section 2.1.3 for calculation and description).

More conventional control variables are *export* intensity, industry *import*s and the *capital intensity* (for definition and more detailed description of the variables refer to Section 2.1.3.1). Clearly, all three variables are also used to represent the competitive environment of a firm and the industry. Information on exports and capital intensity is taken from the MIP survey. The import variable is taken from OECD data and reflects industry imports at the two-digit NACE level. *East Germany* is a dummy variable, which indicates that the firm is situated in the eastern part of Germany (the former GDR). Finally, we add *industry* and *time dummies* as other specific circumstances in an industry and/or cyclical factors, which perhaps are not reflected by our other variables, but may affect returns.

2.2.3. Estimation results

As in Section 2.1.4, we estimate ordered probits with known thresholds. Since the thresholds are known, the variance is identified and can be estimated. Thus, the coefficients can be interpreted as marginal effects. We estimate all specifications twice. First, we investigate the impact factors on firms' profitability including only standard concentration indices (see Table 2.9). In a second step, we include the survey variables regarding the firms' assessment of their competitive situation (see Table 2.10). All specifications are estimated as homoscedastic as well as heteroscedastic model, as in Section 2.1.4. The LR-tests confirms that heteroscedasticity should be accounted for.

According to Table 2.9, neither of the aggregated industry-based concentration indices is significant. Hence, the results presented in Table 2.9 support Schmalensee's conclusion: The impact of concentration is statistically weak, the coefficients have unstable signs, and lose significance if the specification is altered. On the basis of these results, we could reject the hypothesis that there is a relation between market structure and profitability.

The conclusion concerning the effect of imperfect competition is, however, totally reversed if the variables are considered which have been computed using the questionnaire information (Table 2.10 displays the results for the industry- and questionnaire-based variables). The number of competitors has a strong negative impact on profits as predicted by theory. In addition, if the competitors are larger profits of a firm are significantly smaller. Intensive price competition also reduces profits. This is in line with the arguments of Sutton (1991, 1998, 2007). Hence, all competition variables generated on the basis of the survey work excellently. In contrast, the variables based on the official industry classification remain all insignificant, and are clearly dominated by the survey-based variables. We interpret these results as evidence that the official industry classification does not reflect the relevant markets well. If information on the relevant market is available – as perceived by the firms – the expected relation clearly emerges. Hence, the quality of the industry classification and concentration variables calculated on the basis of this information is questionable, as measure for firms' product markets.

Our results also support the frequent application of the price-cost margin as a competition measure. The strong relationship of the price-cost margin with the variables reflecting competitive pressure suggests that the price-cost margin is a reliable measure of competition. Furthermore, firms' profitability is strengthened if barriers to entry exist, represented by other proxy variables. We measure barriers to entry by firms' capital intensity and find a positive effect on profitability. Moreover, the market potential is a crucial factor for firm profitability; demand growth has a significant positive effect on return on sales. Profitability decreases with firm size, which is in accordance with earlier results (Neumann et al. (1979, 1981)). Furthermore, exports generate higher return on sales. Finally, we do not find any evidence that buyer power affects firm profitability.

Table 2.9.: Regression results for conventional concentration indices using homo- and heteroscedastic ordered probits with known thresholds

	Homosc.	**Heterosc.**	**Homosc.**	**Heterosc.**
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
Herfindahl	0.167	0.164	0.067	0.047
	(0.121)	(0.121)	(0.043)	(0.043)
C3 concentration	0.071	0.059		
	(0.086)	(0.085)		
C6 concentration	-0.091*	-0.086		
	(0.055)	(0.053)		
market share	0.106	0.126	0.049	0.066
	(0.090)	(0.085)	(0.088)	(0.083)
demand growth	0.040***	0.038***	0.038**	0.037***
	(0.015)	(0.014)	(0.015)	(0.014)
export	0.018***	0.017**	0.017**	0.016**
	(0.007)	(0.006)	(0.007)	(0.006)
import	-0.005	-0.005	-0.011	-0.011
	(0.017)	(0.016)	(0.017)	(0.016)
capital intensity	0.013	0.016*	0.013	0.016*
	(0.009)	(0.009)	(0.009)	(0.009)
log(employees)	-0.002	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
East Germany	-0.001	-0.000	-0.001	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
constant	0.046***	0.045***	0.036***	0.035***
	(0.010)	(0.010)	(0.009)	(0.009)
industry dummies	*included*	*included*	*included*	*included*
time dummies	*included*	*included*	*included*	*included*
$\hat{\sigma}$	0.052***	0.053***	0.052***	0.053***
	(0.001)	(0.004)	(0.001)	(0.004)
LR(heteroscedasticity) [a]		54.34***		54.18***
χ^2 *(heteroscedasticity)* [b]		26.87**		26.68**
log Likelihood	-5,708.73	-5,681.56	-5,714.43	-5,687.34
χ^2 *(all)* [c]	91.85***	98.35***	86.26***	92.08***
χ^2 *(industries)* [d]	15.12*	28.42**	15.84*	29.50**
χ^2 *(time)* [d]	33.86***	37.06***	34.33***	37.37***
McFadden's R^2	0.008	0.009	0.007	0.008
McFadden's adjusted R^2	0.004	0.002	0.004	0.002
Cragg-Uhler's R^2	0.031	0.033	0.028	0.031
BIC	-12,489.49	-12,494.12	-12,491.05	-12,442.40
Number of observations	3,008	3,008	3,008	3,008

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the coefficients of an ordered probit with known thresholds, i.e. the cutoff points need not to be estimated. Consequently, the coefficients are interpretable as marginal effects like in the linear model. Standard errors are clustered by firm.

[a] LR(heteroscedasticity) is a LR-test with 1 degree of freedom testing whether heteroscedasticity should be taken into account.

[b] χ^2(heteroscedasticity) displays the test of joint significance of the variables determining heteroscedasticity.

[c] χ^2(all) displays a test of the joint significance of all variables.

[d] χ^2(industries) and χ^2(time) display a test on the joint significance of industry and time dummies. For definition of industry dummies see Table A.1 on page 210 in the Appendix.

(Table 2.9 continued)

	Homosc.	**Heterosc.**	**Homosc.**	**Heterosc.**
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
Herfindahl				
C3 concentration	0.006	0.001		
	(0.012)	(0.012)		
C6 concentration			-0.002	-0.005
			(0.010)	(0.010)
market share	0.059	0.078	0.070	0.090
	(0.089)	(0.084)	(0.090)	(0.084)
demand growth	0.043***	0.041***	0.045***	0.043***
	(0.015)	(0.014)	(0.015)	(0.014)
export	0.017**	0.016**	0.017***	0.016**
	(0.007)	(0.006)	(0.007)	(0.006)
import	-0.001	-0.003	0.004	0.001
	(0.016)	(0.016)	(0.016)	(0.016)
capital intensity	0.013	0.016*	0.013	0.016*
	(0.009)	(0.009)	(0.009)	(0.009)
log(employees)	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
East Germany	-0.001	-0.000	-0.001	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)
constant	0.036***	0.035***	0.037***	0.037***
	(0.009)	(0.009)	(0.009)	(0.009)
industry dummies	*included*	*included*	*included*	*included*
time dummies	*included*	*included*	*included*	*included*
$\hat{\sigma}$	0.052***	0.053***	0.052***	0.053***
	(0.001)	(0.004)	(0.001)	(0.004)
LR(heteroscedasticity) [a]		55.46***		56.08***
χ^2*(heteroscedasticity)* [b]		27.38**		27.70**
log Likelihood	-5,715.963	-5,688.23	-5,716.079	-5,688.04
χ^2*(all)* [c]	83.90***	90.22***	83.10***	90.03***
χ^2*(industries)* [d]	15.12*	30.12**	15.84*	30.93**
χ^2*(time)* [d]	33.86***	37.62***	34.33***	37.62***
McFadden's R^2	0.008	0.008	0.007	0.008
McFadden's adjusted R^2	0.004	0.002	0.004	0.002
Cragg-Uhler's R^2	0.031	0.030	0.028	0.030
BIC	-12,490.82	-12,494.12	-12,491.05	-12,442.78
Number of observations	3,008	3,008	3,008	3,008

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of an ordered probit with known thresholds, i.e. the cutoff points need not to be estimated. Consequently, the coefficients are interpretable as marginal effects like in the linear model. Standard errors are clustered by firm.

[a] LR(heteroscedasticity) is a LR-test with 1 degree of freedom testing whether heteroscedasticity should be taken into account.

[b] χ^2(heteroscedasticity) displays the test of joint significance of the variables determining heteroscedasticity.

[c] χ^2(all) displays a test of the joint significance of all variables.

[d] χ^2(industries) and χ^2(time) display a test on the joint significance of industry and time dummies. For definition of industry dummies see Table A.1 on page 210 in the Appendix.

Table 2.10.: Regression results for firms' assessment of competitive situation using homo- and heteroscedastic ordered probits with known thresholds

	Homosc.	Heterosc.	Homosc.	Heterosc.	Homosc.	Heterosc.
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
Herfindahl	0.126	0.127	0.048	0.028		
	(0.119)	(0.118)	(0.042)	(0.041)		
C3 concentration	0.078	0.061			0.002	-0.003
	(0.086)	(0.084)			(0.013)	(0.012)
C6 concentration	-0.091*	-0.084				
	(0.054)	(0.053)				
intensive competition	-0.008**	-0.009***	-0.009**	-0.010***	-0.009**	-0.010***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
intermediate competition	-0.008**	-0.007**	-0.008***	-0.008**	-0.008***	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
competitors size	-0.007**	-0.006**	-0.007**	-0.006**	-0.007**	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
strong price competition	-0.013***	-0.014***	-0.013***	-0.014***	-0.013***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
strong buyer power	-0.002	-0.002	-0.003	-0.003	-0.003	-0.002
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
quite strong buyer power	0.003	0.003	0.002	0.003	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
market share	0.121	0.134	0.068	0.078	0.078	0.090
	(0.093)	(0.087)	(0.092)	(0.085)	(0.093)	(0.086)
demand growth	0.039***	0.038***	0.037**	0.037***	0.041***	0.040***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)	(0.014)
export	0.015**	0.015**	0.015**	0.014**	0.015**	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
import	-0.004	-0.005	-0.011	-0.011	-0.002	-0.004
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
capital intensity	0.013	0.016*	0.013	0.016*	0.013	0.016*
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
log(employees)	-0.002*	-0.002	-0.002	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
East Germany	-0.000	0.000	-0.001	0.000	-0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
constant	0.058***	0.057***	0.050***	0.048***	0.050***	0.049***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
industry dummies	*included*	*included*	*included*	*included*	*included*	*included*
time dummies	*included*	*included*	*included*	*included*	*included*	*included*
$\hat{\sigma}$	0.051***	0.053***	0.051***	0.054***	0.051***	0.054***
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
LR(heteroscedasticity) [a]		59.59***		59.32***		60.48***
χ^2 *(heteroscedasticity)* [b]		29.04***		28.62***		29.23***
log Likelihood	-5,672.08	-5,642.28	-5,677.15	-5,647.49	-5,678.00	-5,647.76
χ^2 *(all)* [c]	129.39**	140.40***	123.43***	133.24***	121.60***	132.18***
χ^2 *(industries)* [d]	14.81*	29.78**	15.90*	30.81**	16.15*	32.16**
χ^2 *(time)* [d]	32.83***	35.93***	32.76***	36.13***	32.95***	36.20***
McFadden's R^2	0.011	0.012	0.011	0.012	0.011	0.012
McFadden's adjusted R^2	0.006	0.005	0.006	0.005	0.006	0.005
Cragg-Uhler's R^2	0.043	0.047	0.041	0.044	0.040	0.044
BIC	-12,514.75	-12,470.22	-12,520.62	-12,475.83	-12,518.93	-12,475.29
Number of observations	3,008	3,008	3,008	3,008	3008	3008

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the coefficients of an ordered probit with known thresholds, i.e. the cutoff points need not to be estimated. Consequently, the coefficients are interpretable as marginal effects like in the linear model. Standard errors are clustered by firm.

[a] LR(heteroscedasticity) is a LR-test with 1 degree of freedom testing whether heteroscedasticity should be taken into account.

[b] χ^2(heteroscedasticity) displays the test of joint significance of the variables determining heteroscedasticity.

[c] χ^2(all) displays a test of the joint significance of all variables.

[d] χ^2(industries) and χ^2(time) display a test on the joint significance of industry and time dummies. For definition of industry dummies see Table A.1 on page 210 in the Appendix.

(Table 2.10 continued)

	Homosc.	Heterosc.	Homosc.	Heterosc.
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
Herfindahl				
C3 concentration				
C6 concentration	-0.005	-0.008		
	(0.010)	(0.010)		
intensive competition	-0.009**	-0.010***	-0.009**	-0.010***
	(0.004)	(0.004)	(0.004)	(0.004)
intermediate competition	-0.008***	-0.008**	-0.008***	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)
competitors size	-0.007**	-0.006**	-0.007**	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
strong price competition	-0.013***	-0.014***	-0.013***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
strong buyer power	-0.003	-0.002	-0.003	-0.002
	(0.011)	(0.011)	(0.011)	(0.011)
quite strong buyer power	0.002	0.003	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
market share	0.089	0.103	0.080	0.086
	(0.093)	(0.086)	(0.090)	(0.083)
demand growth	0.043***	0.042***	0.041***	0.040***
	(0.015)	(0.014)	(0.014)	(0.014)
export	0.015**	0.014**	0.015**	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)
import	0.002	-0.000	-0.001	-0.006
	(0.016)	(0.016)	(0.015)	(0.015)
capital intensity	0.013	0.016*	0.013	0.016*
	(0.009)	(0.009)	(0.009)	(0.009)
log(employees)	-0.002	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
East Germany	-0.000	0.001	-0.000	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
constant	0.051***	0.050***	0.050***	0.048***
	(0.009)	(0.009)	(0.009)	(0.009)
industry dummies	*included*	*included*	*included*	*included*
time dummies	*included*	*included*	*included*	*included*
$\hat{\sigma}$	0.051***	0.054***	0.051***	0.054***
	(0.001)	(0.004)	(0.001)	(0.004)
LR(heteroscedasticity) [a]		61.10***		60.42***
χ^2 *(heteroscedasticity)* [b]		29.56***		29.24***
log Likelihood	-5,677.86	-5,647.31	-5,678.02	-5,647.81
χ^2 *(all)* [c]	121.21***	132.58***	121.13***	132.11***
χ^2 *(industries)* [d]	16.59*	33.11**	16.30*	32.02**
χ^2 *(time)* [d]	49.74***	36.24***	32.93***	36.25***
McFadden's R^2	0.011	0.012	0.011	0.012
McFadden's adjusted R^2	0.006	0.005	0.006	0.005
Cragg-Uhler's R^2	0.041	0.044	0.040	0.044
BIC	-12,519.19	-12,520.62	-12,526.90	-12,483.20
Number of observations	3,008	3,008	3,008	3008

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of an ordered probit with known thresholds, i.e. the cutoff points need not to be estimated. Consequently, the coefficients are interpretable as marginal effects like in the linear model. Standard errors are clustered by firm.

[a] LR(heteroscedasticity) is a LR-test with 1 degree of freedom testing whether heteroscedasticity should be taken into account.

[b] χ^2(heteroscedasticity) displays the test of joint significance of the variables determining heteroscedasticity.

[c] χ^2(all) displays a test of the joint significance of all variables.

[d] χ^2(industries) and χ^2(time) display a test on the joint significance of industry and time dummies. For definition of industry dummies see Table A.1 on page 210 in the Appendix.

2.2.4. Concluding remarks

This section reports the results of a study which employs rarely available variables. We compare the performance of variables which are computed using the official industry classification with the effect of variables generated on the basis of information gathered from the firms themselves. The industry-based variables are concentration indices and the market share. The variables based on the survey information are the number and the size of the competitors, the relevance of price competition and the number of customers.

Our own data clearly outperforms the industry-based variables. While our competition variables have a strong impact on profitability, no relation is found for the industry-based variables. 3-digit industry as the relevant market. The information is too noisy, with the result that no significant relation can be estimated. However, the use of information supplied by the firms themselves can be very useful in explaining profit levels.

While the result with respect to the use of industry data is rather negative, it is quite supportive regarding the theoretical predictions. Profits fall if competitive pressure increases if we use competition measures which reflect the relevant market. Regarding established approaches, we also have good news: Price-cost margins depict quite reliably competitive pressure, and its frequent use is therefore supported by our results.

3. Venture capital in German high-tech entrepreneurship

3.1. Motivation

This chapter investigates the financing of high-technology entrepreneurship, and particularly the impact of a specific financing source, namely venture capital, on firms' decision. We concentrate on two dimensions of corporate decisions: Changing the top management and carrying out innovation activities.

Usually, young high-tech firms have only a limited access to financial markets, particularly to debt markets. The relation with the investor is characterized by substantial information asymmetries because young firms are usually not able to reliably signal their quality and the abilities of the top management, e.g. those firms have no track record and their most valuable asset – which is knowledge – is intangible and of small collateral value. Besides capital, young high-tech firms also lack management skills since it is assumed that academics with technical background often make bad managers. In such a setting, venture capital is often seen as a last resort since those investors are able to provide substantial amounts of capital as well as management support which usually includes influencing firms' decisions. The most drastic action, which a VC investor may execute, is to change the structure of the top management team. Section 3.4 investigates the impact of VC financing on changes in the executive team and the subsequent impact on firm performance[9].

Influencing the composition of the top management is an important scope for investors. Dembkowski (2007) presents results of 20 qualitative interviews with institutional investors and private equity companies, operating in Frankfurt and London, and concludes that German top managers fail. The message of the study is that those investors

[9] Section 3.4 is inspired by and partly based on the idea presented in Heger and Tykvová (2007).

are not content with the quality of the top management of German firms. In order to obtain their expected yearly return on investment, the institutional investors take care about the qualification of the top management and push for an exchange when they detect any failures.

What happens with top managers in young high-tech firms? Which role do VC investors – as a part of the private equity market – play in this setting? Does performance improve subsequent a change in the top management? VC investors generally invest in young firms with a high potential. As active investors, VC companies (VCCs) support the firms' management. Whereas most of the VC companies' day-to-day activities remain unobservable, one of the most striking actions, namely the decision to change the structure of the initial executive team, is distinctly apparent. The VC companies' right to influence the structure of the executive team is a typical part of the contract concluded between the VC company and the investee firm (Hellmann (1998), Hellmann, Puri (2002), Baker, Gompers (2003)).

Replacement within the management team is usually justified by the underperformance of the current team. Compared to other investors, VC companies may be especially "impatient" regarding performance because their main goal is the generation of high returns. Furthermore, their investment horizon is quite short-term – between 3 and 7 years (see Cumming, MacIntosh (2003)) – which increases the "impatience". This may lead to what Rosenstein et al. (1993) observe: "At one end of the spectrum, venture capitalists incubate start-ups and nurture hatchlings, while at the other extreme, so-called 'vulture' capitalists feed on fledgling companies.".

Another strategic decision of high-tech entrepreneurial firms, on which VC investors may have an influence, is the innovation decision. Evidence for German high-tech entrepreneurship is provided in Section 3.5. The starting point is that venture capital is often perceived to spur innovation. Anecdotic evidence exists, particularly for the U.S., where today's big players in innovative markets, like computer or biotechnology markets, have been VC-financed in their early stages. Prominent examples are Apple, Microsoft and Genentech.

Section 3.5 tries to clarify whether the provision of venture capital has a positive effect on firm's innovation activities. Innovation activities are first proxied by the number of patents. In the literature, the use of patents as an indicator for innovation is discussed since patents only display innovation output to a certain extent because not all output is patentable or patented. The second proxy of innovation activities is a categorial variable named innovativeness. This measure indicates if the firm's most important product or service embodies methods and technologies that are totally new, either developed by the firm itself or by a third party, or if the product or service comprises an innovative or a known combination of tried and tested methods and technologies.

A problem with respect to VC financing is the fact that VC financing may be endogenous. Endogeneity may arise because receiving VC financing is not random but the result of a substantial screening and due diligence process. By this means, VC investors are supposed to "pick the winners", i.e. strongly select investment opportunities which they expect to be successful.

The chapter first describes the financing problem of young high-tech firms and venture capital as a remedy for it. The following section gives a general overview of the literature concerning VC financing including the relevant literature regarding VC companies' influence on executive turnover (Section 3.2.2.1) and innovation decision (Section 3.2.2.2); the starting points of the empirical analyses carried out in Section 3.4 and 3.5. Section 3.3 describes the data set used throughout the empirical analyses of Section 3.4, in which we analyze the determinants and consequences of executive turnover, and of Section 3.5, which investigates VCCs' impact on firms' innovation activities.

3.2. Literature review

3.2.1. The financing problem of young high-tech firms

Technology-oriented firms are supposed to transform new knowledge generated in research processes, e.g. in research institutes, to market-compatible products. Thus, they contribute to the economy's prosperity, growth and competitiveness (Carpenter, Petersen (2002)) and are often viewed as a source of radical technological innovation and employment growth (Timmons, Bygrave (1986)).

But young high-tech firms often report problems in financing their projects. In the literature on entrepreneurial finance, the term "finance gap" or "funding gap" is often used. This term has first been raised by the report of the MacMillan Committee in 1931 (see Stamp (1931)). It is described as a situation where a firm has grown to a certain size by making maximum use of short-term finance but is not yet big enough to approach the capital market for longer-term finance.

3.2.1.1. Theoretical framework

A common starting point for the discussion about corporate finance and investment is the so-called Modigliani-Miller theorem (Modigliani, Miller (1958)): For investment decisions, the firm's capital structure, and hence, the source of finance, is irrelevant, i.e. the price of capital is the same for all investments – internal and external capital are perfect substitutes. This stylized result is based on restrictive assumptions, like perfect capital markets and the absence of taxes, information costs, bankruptcy costs and transaction costs. Since capital markets are not perfect, adverse selection and moral hazard have to be addressed. Investment decisions may depend on specific factors like the availability of internal finance, access to debt or equity finance or the functioning of particular credit markets (Fazzari et al. (1988)).

Financial contracting theory analyzes the determinants of how firms finance their investments and operations. Therewith, contracts in this respect can be interpreted as securities issued by the firm. Investors provide funds expecting to share in the returns generated by the investments of the firms and knowing that the returns depend on firms' decisions. Therefore, the design of financial contracts includes the allocation of cash flow and the assignment of control rights (Harris, Raviv (1992)).

The literature of financial contracting can be divided into two strands: Models based on principal agent theory and models dealing with asymmetric information. Models based on agency costs are initiated by Jensen and Meckling (1976). They show that agency problems, that arise due to the separation of ownership and control (Berle and Means (1932)), may influence the outside capital provision for both debt and equity capital. Since capital providers recognize the moral hazard problem, investors require a higher rate of return with respect to internally generated funds. Security design models solve agency problems between managers and outside investors by addressing the allocation of cash flows (see e.g. Diamond (1984), Gale, Hellwig (1985)).

In the literature of contract theory, two approaches are identified that may help to decrease agency problems in situation as described above (van Osnabrugge (2000)). The first concerns the optimal contract design between the principal and the agent (Jensen, Meckling (1976)). Within this framework, screening costs are accepted in order to reduce information asymmetries. The contracts are more comprehensive and aligned to influence the agent's behavior. They are usually based on behavior or outcome. Second, the incomplete contracts approach (Hart (1995a, 1995b)) conceives that contracting is costly so that a contract is never complete. Hence, the ex post allocation of power and control is more relevant than the ex ante screening process. According to Hart (1995a), contracting costs are considerable and arise because of the presence of transaction costs, bounded rationality and asymmetric information. As a consequence, renegotiation should be possible if new information arises. Since returns are not contractible, "incomplete" contracts are written on assets, so that one source of control is the possession of firm's residual control rights. Van Osnabrugge (2000) states that in the context of small firms, particularly start-ups, firm assets may not be attractive for investors. Especially, if small firms act in a highly risky environment, ex post control and the exertion of power over the investment may best be achieved by the investor's active involvement. In subsection 3.2.2, we will see that VC contracts incorporate elements of both approaches: substantial screening and effective involvement.

Models focusing on asymmetric information between managers and investors usually deal with the lemons problem first formulated by Akerlof (1970). One result of the financial contracting literature in this field is that insider information can be signaled to outside investors by the choice of the capital structure (Leland, Pyle (1977)). Myers and Majluf (1984) and Greenwald et al. (1984) show that the provision of internal equity is a positive signal to the market. An increase in equity capital achieved by the issuance of new shares is interpreted as a negative signal. Another application of information asymmetry to the corporate finance of innovation activities is the so-called pecking order model (Myers (1984)) which conjectures that external financing is costly and firms attempt to maintain the maximum level of autonomy against banks and financial markets, even if the choice is suboptimal. Myers (1984) concludes that firms prefer internal finance to debt and debt to equity finance[10].

[10] A preference of equity over debt is, however, recommended by the transaction cost approach (Williamson (1988)).

3.2.1.2. Financing of innovation activities

Throughout this chapter, we focus on high-tech start-ups which are assumed to be innovative. Financing of innovation and R&D activities can be viewed as an investment in the future of the firm since innovation activities are supposed to strengthen the firm's competitive position and performance, and contribute to future profits (Hall (2002)). However, Arrow (1962) postulates that innovation activities are usually not adequately financed, i.e. firms do not invest enough funds. The reasons are mainly linked to the characteristics of the output, namely knowledge, which exhibits some characteristics of public goods. As a result, the returns on innovative activities cannot be fully appropriated by the innovator because of the nonrival character of knowledge.

The innovation process is characterized by a high level of uncertainty. It begins with an idea which is researched and developed according to a process of trials and errors. Stevens and Burley (1997) estimate that on average 3,000 raw ideas are tried and tested to get one major commercially successful innovation. Thus, output is characterized by uncertainty which concerns the unpredictability of the result and the time scale for product delivery (see Hall (2002, 2005), Arrow (1962)).

Usually, the innovation process is characterized by highly specific investments which are not easy to redeploy (Alderson, Betker (1996)), and thus increase losses for the investor in the case of default. For example, a major part of R&D investments are wages and salaries for highly educated R&D employees, like scientists and engineers. Consequently, the innovation process cannot be easily altered which causes R&D spending patterns to be similar to investments with high adjustment costs (Hall et al. (1986), Lach and Schankerman (1988), Hall (1992)). Adjustment costs in this case may arise because the newly generated knowledge is often tacit, firm- and product-specific and is largely incorporated in the R&D employees. Thus, firing R&D employees results in a loss of knowledge which cannot easily be transmitted to, or regenerated by newly hired R&D employees (Harhoff (1998), Himmelberg, Petersen (1994), Hall (2002, 2005)).

Moreover, innovative products are novel and consequently untested in markets. But the attractiveness of the market is a crucial parameter for the prospective investor's decision because it is an indicator of the expected return (see for example Bandulet (2005), Baier, Pleschak (1996), Lessat et al. (1999)). As a consequence of the longsome R&D

process and product novelty, the returns to high-tech investments are skewed and highly uncertain (Cassar (2004), Moore (1994)).

As described in the previous subsection, the Modigliani-Miller theorem predicts that external and internal financing sources are substitutes, but there are some reasons why the costs of external and internal capital may fall apart in the case of innovation investments. Agency problems arise in this context because of the separation of ownership and control and the resulting moral hazard problems. Furthermore, the relationship between the inventor and the outside financier is characterized by asymmetric information since the inventor has better information about the quality of the innovation. Even if reduction of information asymmetries was costless, firms would be reluctant because of strategic considerations (Himmelberg, Petersen (1994)). This results in a higher lemon premium for the external financing of R&D investments (Leland and Pyle (1977)). Applying the pecking order model of Myers (1984), this statement leads to a preference for internal funding of innovation activities. If R&D activities were only financially feasible by relying on internal funds, firms in competitive markets could not be able to gather enough profits. Thus, at least temporary monopoly profits would be necessary in order to assure adequate R&D funding (see also Schumpeter (1934, 1939, 1942) on this issue).

In line with these theoretical results are the findings of the literature investigating whether R&D investments are financially constrained. Leland and Pyle (1977) and Bhattacharya and Ritter (1983) show that, due to moral hazard problems in the relation between entrepreneur and investor, R&D investments are constrained by cash flow. Himmelberg and Petersen (1994) and Hall (1992) find a substantial effect of internal finance on R&D investment. The importance of positive cash flow is particularly pronounced for R&D investments compared to other types of investment. Harhoff (1998) confirms an effect of cash flow on R&D activities in Germany whereas Bond et al. (2003), comparing British and German firms, find only a significant effect for British firms which do not perform R&D. Mulkay et al. (2001) ascertain impacts of cash flow on R&D and ordinary investments for the US and France. Bourgheas et al. (2003) detect that R&D investments are financially constrained in Ireland. This underlines the view that internal finance is often seen as the best funding source for R&D activity.

3.2.1.3. Characteristics of young high-tech firms

The findings concerning the financing of innovation are mainly derived for large firms. Focusing on high-tech entrepreneurship and its problems of adequately financing R&D and innovation activities, young high-tech firms are not able to rely more or less exclusively on internal funds because they are obviously not able to redeploy profit retentions. The only internal sources on which high-tech entrepreneurs may be able to rely are his own funds and capital of family and friends.

There is evidence that the available financial sources of the R&D process depend on firm size. Large firms prefer internal R&D expenditures, whereas SMEs rely to a larger extent on external financial sources. Hence, small and medium-sized firms are more likely to encounter financial constraints compared to large firms which is particularly true for high-tech industries (Audretsch, Vivarelli (1996), Acs, Audretsch (1990)).

In the context of young high-tech start-ups, the information asymmetries relate to the ex ante evaluation of the project and the entrepreneur (adverse selection), and to the ex post monitoring of performance (moral hazard). These information asymmetries exist for both large and small firms but they are particularly prevalent for small firms because of the anticipated higher costs of information collection: The fixed costs of gathering information is high relative to the investment, and small firms have fewer instruments to signal their quality than large public firms because the latter are forced by legislation to publish balance sheet information. Hence, the current situation of the firm is known to a certain extent by the external investors (Ang (1991)). Information gathering is even more difficult in the case of growing firms because of the pace of change within the business and the associated changing challenges (Binks and Ennew (1996)).

High-tech firms are often seen to be innovative which gives rise to an additional source of risk which emanates from the staged development of young, innovative SMEs reflecting the complex innovation process. This process begins with the initial concept of a product, continues with prototype development, initial production, and finally, product sales. The financing of this process requires a series of injections of money. Any part of the cycle needs to be financed adequately, if this is not the case it may cause the firm to fail (Bank of England (2001)). Furthermore, the degree of risk and financial requirements of entrepreneurial firms in high-risk industries depend on the stage of development. In the pre-founding seed stage, risk is extraordinarily high while financial need are modest and mainly focus on the assessment of the business idea's potentials with respect to economic and technological feasibility. In the early stage, particularly in the start-up stage the degree of risk is still fairly high but financial requirements augment substantially. In the early and sustained growth stages, risk is modest and financial requirements decrease moderately (see e.g. Sau (2007)).

Moreover, high-tech products and services tend to be of shorter life than in the more conventional sectors which crucially impacts on firms' profitability (Moore, Garnsey (1993), Storey, Tether (1998)). In addition, the management team depends on a few key individuals and may lack some crucial characteristics (Cassar (2004), von Glinow, Mohrman (1990), Moore (1994)). Additionally, R&D activities are knowledge- and labor-intensive and crucially require highly qualified and skilled employees. In this domain, young technology-oriented firms may be less able to attract this scarce factor (Pleschak, Werner (1999)) because they cannot assure a suitable remuneration and career scheme as large firms do.

Myers (1984)'s pecking order (see Section 3.2.1.1) gets somewhat reversed if small, young and innovative firms are focused. Aghion and Bolton (1992) model a pecking order theory for control structures in contracts between entrepreneurs and investors. As a result, the entrepreneur prefers contracts in which he retains the most control, i.e. he prefers non-voting equity to debt or convertibles to voting equity.

As a consequence of the firm-specificity, intangibility, the limited collateral value of high-tech investments and the restricted internal funds (Carpenter, Petersen (2002), Carpentier, Suret (2005), Berger, Udell (1998)), it is particularly difficult for small high-tech firms to get debt financing since the investors are aware of these problems. Carpenter and Petersen (2002) provide reasons why the extensive use of debt finance is even inappropriate for high-tech firms and why their shadow cost of debt finance may increase rapidly with higher leverage. First, the provider of debt financing is aware of the problem that he would not share in firm's returns if the firm was successful and generated extremely high returns, but he has to bear the full risk of failure. Or in Stiglitz (1985)'s words 'lenders are only concerned with the bottom part of the tail of the distribution of returns'. Second, the adverse selection problems in debt markets are even more distinct for high-tech investments because of the higher uncertainty about the returns, the likelihood that firms have better knowledge about the inherent risk of their projects and because of credit rationing (for the general model see Stiglitz and

Weiss (1981), also Bester and Hellwig (1987)). Third, debt financing may lead to moral hazard problems, i.e. to ex post changes in behavior, by substituting high-risk for low-risk projects (Carpenter, Petersen (2002)). The expected marginal costs of financial distress are likely to rise rapidly with higher leverage since financial distress can lead to the loss of key employees and the abandonment of critical projects (Carpenter, Petersen (2002)). Following Gompers (1994), those firms face many years of negative earnings, and during that period, they are unable to make interest payments on debt obligations since debt usually requires constant payments. Therefore, the need of a stable source of cash flow is needed (Hall (2002)) which R&D-intensive firms often do not generate, particularly, if they are small. Additionally, they exhibit a higher default risk (Fritsch et al. (2006)).

The investor's uncertainty problem is particularly linked to the analysis of the technological feasibility, the growth potential and the existence of a sufficiently large and attractive market which are difficult to assess for an external investor (Murray, Marriott (1998), Storey, Tether (1998)). Consequently, start-up firms in high-tech sectors often rely on risk-bearing capital. Therefore, external equity is often seen to be an adequate funding scheme, and is in many cases the last resort for young technology-oriented firms.

3.2.2. Venture Capital Financing

The VC industry lacks a precise legal or regulatory definition. In the economic literature, four characteristics are usually named: VC companies finance *high-risk* and *potentially high-rewarded* projects where the underlying ideas or products are unproven. VC companies purchase *equity or equity-linked stakes*, e.g. long-term convertible debt, while the firms are *still privately held*. Moreover, VC companies are intermediaries between investors and entrepreneurs, i.e. they conclude contracts with outside investors, from whom the VC companies raise funds, and with the entrepreneurial venture, in which they invest. Thus, investments of the VC companies involve a two-sided principal-agent relationship: One as principal with the entrepreneurial firms and the other as agent with the end-investors (Sahlman (1990)). The main difference between VC and other forms of financial intermediation is the combination of equity participation and active involvement in the firm (Brander et al. (2002)). Thus, VC companies can be described as hands-on investors developing expertise in specific lines of business (Casamatta, Haritchabalet (2003)). The VC companies' main objective is to maximize the investors' returns (Weber, Dierkes (2002)). Furthermore, the definition of VC may also be linked to the firm's lifecycle. Sahlman (1990) states that VC should be regarded simply as equity-like investments in the early and expansion stages, whereas Bygrave and Timmons (1992) also include management buyout and buyin.

Both roles of VC companies, i.e. the advising/involving and the financing, are complementary since they arise in the context of incentive problems (Repullo, Suarez (2004)). Kaplan and Strömberg (2004) define four issues of information asymmetries during the VC investment process: First, a moral hazard problem arises since the entrepreneur's effort is not observable. Second, adverse selection may be an issue since the entrepreneur is better informed about his abilities and qualities. Third, VC companies anticipate that there may be situations in which the VC investor and the entrepreneur disagree. From a control theory perspective like in Aghion and Bolton (1992) and Dewatripont and Tirole (1994), control should then be assigned to one of the parties according to the state of the firm. And finally, the VC companies are aware of a hold-up problem when the entrepreneur is supposed to leave the venture knowing of the crucial importance of the knowledge he incorporates.

VC companies use different mechanisms to deal with these information asymmetry problems. First, they impose *high expected rates of return*, particularly for early stage investments (Murray and Lott (1995)). Mason and Harrison (1999) estimate that established companies need to generate annual internal rates of return of at least 30 %, rising to 60 % or more for seed/start-up investments. But claiming high prices for the investment may cause adverse selection on the side of the entrepreneurial firms.

Second, the *evaluation or screening* of investments plays a substantial role. Amit et al. (1990) show in a model that adverse selection could be diminished if signals certifying either the quality of the entrepreneur or his confidence in the success of the project are applied. Several studies examine criteria used by venture capitalists to screen their potential investment opportunities (Kaplan and Strömberg (2000)). Earlier papers suggest that the key criteria for early-stage investments relate to the business experience and personality of the entrepreneur, issues associated with the product and market appear to be less important. Whereas findings of more recent studies conclude that industry and market factors are more important than the entrepreneur and his team (see for example Franke et al. (2006), Eisele et al. (2002)). This combination of extensive screening and high hurdle rates results in a rejection of most of the proposals. Fenn et al. (1995) estimate that only 1 % of the projects obtain financing.

Third, the *contract* concluded between VC companies specifies the rights of the parties and the basis on which their performance is monitored and rewarded. A classification of the various possibilities is given by Berger and Udell (1998). If the VC company is assigned extensive control rights over the firm, this prevents hold-up situations as described above. Hellmann (1998) models the allocation of control rights in VC contracts and states that this provides the VC company with incentives to look for superior management teams. Kaplan and Strömberg (2004) show that the management intervention of VC firms is related to its board control while the equity ownership of VC companies determines its advising and supporting function.

One possible feature of a contract is the *staging* of investments, i.e. a new injection of funds only occurs after the firm has attained a previously defined milestone. Staging helps to ensure the optimal exercise of production options and efficient development and termination of projects (see also Admati, Pfleiderer (1994), Bergemann, Hege (1998), Cornelli, Yosha (2003)), to lower agency costs (Gompers (1995)) and to avoid hold up situation by means of renegotiation from the part of the entrepreneur (Neher (1999)). Repullo and Suarez (2004) focus on incentive problems and staging of financing and find that the optimal contract resembles much the securities employed by VC investors.

The alignment of incentives through appropriate *remuneration and bonding strategies* may be given by performance-related pay structures and share option schemes for entrepreneurs (see Bergemann and Hege (1998) for a model). These compensation schemes, including provisions for the replacement of underperforming entrepreneurs, are also an important component of the venture capital contract (see Sahlman (1988, 1990)), as well as restrictive covenants (Chan et al. (1990)), board representation (Lerner (1995)), the allocation of voting rights (Fenn et al. (1997)) and replacing the original founder (Hellmann (1998), Hellmann, Puri (2002), Baker, Gompers (2003))[11].

Fifth, the use of *quasi-equity* rather than full equity finance will enable the venture capitalists to reduce agency problems, and to deal with the inhering product and market risk (Gompers, Lerner (1999), Liles (1977), Brander et al. (2002)). Common instruments

[11] VCCs' right to replace the executives is a typical part of contracts between the VC and the company. See e.g. Sahlman (1990) and Tykvová (2007) for overview articles on contracts between VCCs and the entrepreneurial firms and refer to Section 3.2.2.1 and the analysis in Section 3.4.

are preferred and /or convertible stocks (Kaplan and Strömberg (2000)) because they enable venture capitalists to allocate cash flow, voting, board and liquidation rights, to exert appropriate control over entrepreneurs and to take precedence over any ordinary shareholders. Trester (1998) shows that this limits the entrepreneurs' incentives to behave opportunistically under conditions of asymmetric information. Convertible preferred stock is especially wide-spread in high-tech industries because in the early stage when the main business is research and development the entrepreneur is often the only one who is able to observe and assess the outcome whereas later stages may be more readily assessed by outsiders like external investors (Brierley (2001).

Finally, VC companies monitor the entrepreneurial firm after the investment and mentors it. The assistance of VCCs in the firm also includes industry contacts in the various markets in which the firm operates by providing credibility, expertise and contacts (Rock (2002)). For example, in the product market they assist in making customer introductions, or in the labor market in identifying and hiring critical personnel (Bygrave, Timmons (1992)), as well as in the capital market in raising additional financing by providing certification to outside investors by means of accumulating private information (Gorman, Sahlman (1989)). VC companies help in identifying strategic partners and suppliers, acquiring other firms or being acquired by them (Rock (2002)), and finally, determine the optimal timing of public offering or sale (Lerner (1994)). Gompers (1995) find that the frequency of VC companies monitoring rises if increasing agency costs are expected. This is particularly the case when the assets are intangible, the growth option higher or the asset specificity is larger.

A characteristic of VC financing is often the syndicated investment of several VC companies in one project in order to share or to reduce risks. The risk sharing argument is linked to the traditional diversification argument whereas risk reduction can be associated with the resource based view since VC companies are supposed to also provide non-financial assets to the firm. Lockett and Wright (2001)) find that the motives for syndication are driven by financial considerations, i.e. by the risk sharing argument. Admati and Pfleiderer (1994) argue that syndication may also arise because of information asymmetries between initial VC investors and potential investors in later stages. Syndication is in this respect a means of avoiding opportunistic behavior, and thus, signalling a good quality of the investment. Hence, two conflicting hypotheses exist regarding VC syndication: The selection hypothesis predicts a better performance of projects financed by a single VC firm than by a syndication while the value-added hypothesis leads to the opposite argumentation. The selection hypothesis assumes that the VC investor is able to identify high, middle and low quality firms and will finance high quality firms whereas for the middle-quality the VC firm may want to consult other VCCs. As opposed to this, the value-added hypothesis states that syndicated investments offer improved managerial support, higher reputation and more contacts than single VC investors.

As stated above, VC investors are strongly return-oriented. Since equity investors usually generate return by divesture, attractive exit routes for investments in young and risky firms are a crucial component of a well functioning VC market. According to a model of Bascha and Walz (2001), the first best solution is to use an initial public offering (IPO) for firms with large values and trade sales for those with low values. The possibility of IPOs for relatively young firms is often seen to be a main driver for the development of functioning VC market (Jeng and Wells (2000), Gompers (1998)). Usually, an IPO generates very high returns for the investors. But entrepreneurs may benefit from IPOs as well, since the IPO enables the entrepreneur to reacquire control over the firm. This may increase the incentives to invest as much effort as possible in order to increase the value of the firm (Black, Gilson (1998)). Furthermore, in cases in which the future value of the firm depends on human effort and risk taking, the entrepreneurs may prefer IPOs in order to reduce the bargaining power of outside equity investors (Myers (2000)). Cumming and Macintosh (2003) find that exit efficiency crucially depends on the quality of the firm, the nature of its assets and the duration of the venture capital investments whereas IPO is often used for the highest quality firms (see also Bygrave, Timmons (1992)).

3.2.2.1. VC companies' impact on changes in the executive team

This section reviews the literature concerning the influence of VC companies on the composition of the executive team and the link of executive turnover and firm performance, which is investigated in Section 3.4.

First of all, we shortly discuss the reasons for executive turnover. There exists a broad strand of literature which deals with the turnover of executives but presents theory and evidence only for large, established – and mainly public – firms. In this context, the dismissal of executives is assumed to lead to strategic reorientation of and reorganization within the firm (Denis, Denis (1995)). But there may be different aspects of CEO succession for start-up firms. Wasserman (2003) discusses three of them: First, the starting point of most studies dealing with CEO turnover is the concept of separation of ownership and control proposed by Berle and Means (1932). This concept applies best to large, public firms for which dismissal is a means to align the incentives of the managers with the aims of the owners, and hence to avoid agency problems (Jensen, Meckling (1976)). But at the time of firm foundation the founders manage the firm, and usually, own all equity. Mostly, they first give up equity stakes when they accept outside investors to fund – at least – partly their projects (Wasserman (2003)). Even more mature entrepreneurial firms exhibit a larger ownership of the founder CEO than large public firms (Wasserman (2001)). Second, founding executives differ in many ways from professional CEOs who may join the company later: Their identification with the firm is larger (Dobrev, Barnett (1999)). Furthermore, founding executives are generally younger, and have less years of work experience. They are paid lower salaries, and own substantially more equity (Wasserman (2001)).

Third, a central issue to the success of changes in the executive team is taken by the insider-outsider discussion where outside successors are assumed to be more independent of the established organization. Hence, they are more likely to introduce organizational changes which are conjectured to have positive effects on performance (Gouldner (1954)). This discussion does not apply to succession in start-up companies since the successor almost always comes from the outside of the firm – there are less inside candidates. This view is supported by Reinganum (1985) and Helmich (1977).

There are some studies pointing at reasons why in entrepreneurial firms – and particularly, in high-tech industries – changes in the top management may be inevitable. The challenges, which the executive teams face, may change depending on the stage of the firm. Usually, founders of high-technology firms had a scientific career – predominantly technical – but lack managerial and/or entrepreneurial skills (Cassar (2004), Moore (1994)). It is widely assumed that academics with a technical background rarely make good managers. During the start-up phase, their technical knowledge is decisive, particularly for the development of market-compatible products. But in later stages like early growth and developing maturing periods, their skills may get redundant when production and marketing knowledge is crucial for the firm's success (Cressy, Hall (2005), Wasserman (2003), Moore (1994)). Wasserman (2003) analyzes founder CEO succession with a set of 202 internet firms using an event study. He finds that the rate of succession increases after the completion of product development. After the successful foundation of the firm, the founding executives must prove whether they still have the necessary portfolio of skills, experience and credibility to adapt and lead the firm through the subsequent stages of firm development. Empirical evidence shows that many of the founding managers are replaced within the first 7 to 8 years by professional, i.e. experienced managers (Cressy, Hall (2005)).

Next, we have a look at the literature, regarding the impact of VC companies on changes in leading positions. Previous literature mostly concentrates on the influence of VC companies on the composition of the board of directors. The results suggest that their impact is decisive for turnover. VC investors may be concerned about the tradeoff between incentives and control influenced by the extent of executives' equity stakes. As VC companies are diversified, they require repeated access to capital markets, do not have private benefits of control, and therefore have a strong motivation to improve governance, and reduce control in order to maximize the IPO prize, and hence their return (Baker, Gompers (1999)).

Rosenstein et al. (1993) investigate 162 VC-backed high-tech firms in California, Massachusetts and Texas and classify the lead VC investor on the boards according to whether they were a “top 20” firm. They find that board size increases substantially with the first investment by VC companies. Furthermore, they demonstrate that the VC companies' managing partners are often present on the board of directors. Lerner (1995) bases his investigation on a data set of 307 VC-backed biotechnology firms assembled by Venture Economics[12]. The results show that the distance between a VC company and the investee firm is an important determinant of VCCs' board membership. The larger the distance is, the lower the probability of a representative of the VC investor joining the board. Furthermore, the level of involvement is influenced by the stake held by the VC company (Lerner (1995)).

Boone et al. (2006) examine changes in the board within the subsequent 10 years after an IPO and confirm the impact of VC companies on board composition. In particular, venture capital financing leads to a larger fraction of outside directors. Baker and Gompers' (2003) finding support the higher proportion of independent outside directors in VC-backed firms using a data set for 1,116 firms for which they gathered information from the IPO prospectuses. The find that the probability that the founder remains CEO

[12] Venture Economics is a provider of information and analysis on the VC industry located in the U.S. The data gathers information on privately held and VC-backed firms between 1978 and 1989

at the IPO decreases as the VC company's bargaining power increases, using the VC company's reputation as a proxy for bargaining power.

Finally, Hochberg (2006) examines the effects of pre-IPO venture capital backing on the corporate governance of the IPO firm and how governance and monitoring differ comparing VC- and non-VC-backed firms. He concludes that, after the IPO, VC-backed firms have boards of directors which are more independent from the management than similar non-VC-financed firms. This also translates in a more probable separation of the roles of the CEO and the chairman.

Some papers focus on the role of VC investors on the dismissal of CEOs. A paper closely linked to the first part of Section 3.4 is Hellmann and Puri (2002). They use a hand-collected data set of 170 Silicon Valley start-ups and test whether VC firms influence the professionalisation of the new companies, i.e. the development of the firms. They distinguish between the roles of VC companies in the internal organization of the investee firm, such as the recruitment process and the appointment of the CEO. Hellmann and Puri find that VC-backed firms experience replacement of the founder by an outside CEO more probably and also earlier than non-VC-backed firms (see also Wasserman (2003)).

Another reason why young firms more often experience changes in the founding executive team when they are VC-backed may also be connected to the reluctance of outside managers to take a leading position in a firms at an early stage. This reluctance may be explained by the high risks at the early stages of a high-tech venture, and the fact that the firm has usually not yet proven the success of its business strategy. In such situation, the presence of a VC company as investor may help to attract outside CEOs since this may be a signal of firm quality to the prospective manager (Hellmann, Puri (2002)).

Another closely linked paper is the study by Kaplan and Strömberg (2004). They try to expand the research on differences between the intervening and the supporting role of VC investors by assessing the investment memoranda of 11 VC companies investing in 67 firms. They show that VC investors take actions which are related to the terms of contract. One result is that at least half of the VC companies expect to play an important role in recruiting and changing the management team.

Several theoretical models exists dealing with the topic of founders' replacement in the VC context. The central issue of the model by Hellmann (1998) is the VC companies' right to dismiss founders who may increase their private benefits at the expense of firm profits. This right is not state contingent, independent of the financial structure and disciplines the founder. Hellmann derives the optimal contract and shows that it induces a positive rate of replacement. Compared to Aghion and Bolton (1992)[13], Hellmann examines the case where the firm is able to generate the investor's required return without relinquishing control. In Chan et al. (1990)'s model, the VC company becomes the new manager after the dismissal of the original founder. In this setting, replacement is more likely if the founder is less productive in comparison to professional managers, if the private benefits of the founder, are lower and if the VC company has greater bargaining power.

Bergemann and Hege (1998) model a learning process and a moral hazard problem for a project financed in stages in a multi-period framework. The founders control the allocation of the capital provided by the VC company and may divert the funds to their private consumption. This diversion cannot be observed by the VC firm. Bergemann and Hege find that if the VC company is in a position to monitor or to replace the founder, the efficiency increases.

Cressy and Hall (2005) investigate the question at what point a venture capitalist should replace an owner-manager. They develop a model in which the managers of VC-backed firms are of unknown quality, and the VC company receives in each period a performance-related informative signal. Replacement of the owner-manager takes place when he underperforms. The model predicts that the probability of replacement increases with the monitoring costs, the productivity of substitute managers and the discount rate of the VC, and decreases in the quality of the manager's track records. Cressy and Hall test their model empirically for high-tech venture capital investments and find that replacement is more likely with increasing monitoring costs and VC's share whereas patent application lowers the probability of replacement which is in line with the theoretical predictions.

As concerns the link of changes in the top management and performance, a large body of literature exists regarding the influence of firm performance on the turnover in the executive team. The theoretical background of this strand of research is the principal-

[13] Aghion and Bolton (1992) are concerned about the conditions for the entrepreneur relinquishing contingent control, i.e. the investor obtains control only in some states of the world.

agent theory which applies best for firms exhibiting a separation of ownership and control, i.e. predominantly large firms. Theory predicts that the threat of dismissal in case of poor performance may provide an incentive for the CEO when deciding on how the firm should be run (Holmström (1979)). Most papers find an inverse relation of firm performance and CEO turnover indicating that poor performance increases the likelihood of turnover (see e.g. Coughlan, Schmidt (1985), Warner et al. (1988), Weisbach (1988), Jensen, Murphy (1990), Barro, Barro (1990), Kaplan (1994), Huson et al. (2001), Lausten (2002)). It is widely assumed that firm performance is influenced by the skills of the managers, particularly by their capabilities in managing people and by their knowledge about market, technology and competitive environment (Cressy, Hall (2005)). Consequently, firm performance provides a signal of the executives' ability which is not observable for outsiders and influences the likelihood for the CEO to be replaced; although performance may be a spurious indicator for executives' abilities since performance is not fully influenceable by the executive but also depends on other unobserved factors (e.g. Weisbach (1988) provides empirical evidence).

Furthermore, Weisbach (1988) shows that CEO turnover is more sensitive to firm performance when the board is dominated by outside directors compared to insider-dominated firms. A similar argument applies to outside shareholders. Hermalin and Weisbach (2001) state that the relation between performance and CEO turnover may also be influenced by outside shareholders having a more distant look on the firm and a sense of failure. This is particularly true regarding VC companies – either as representatives at the board or as outside shareholders. Adams et al. (2005) investigate whether variability of firm performance depends on the distribution of decision-making power. They find that it is higher for firms in which the CEO has larger power on decision making compared to firms in which decision making is based on the consensus of the top management.

The literature regarding the opposite direction of the consequences of executive turnover on firm performance is not huge. Khurana and Nohria (2000) list three possible outcomes for performance subsequent a CEO dismissal: First, the impact is negative if the change is disruptive regarding the firm's processes and routines. A positive effect is expected if the CEO is replaced by decision makers who are better able to deal with distress (Pfeffer, Salancick (1978)). Virany et al. (1992) state that this organizational disruption may lead to performance improvements when altering internal organizational dynamics. Finally, no significant effect is found if performance is influenced by processes which are or cannot be controlled by managers (Gamson, Scotch (1964)). Empirical evidence is ambiguous. A positive reaction of the stock market to CEO dismissals can be found (Denis, Denis (1995)) as well as negative effects (see Grusky (1963) for evidence regarding coach turnover in baseball teams) as well as no effect. Reinganum (1985) finds that, in small firms, changes in the executive team have a positive impact on performance. Khurana and Nohria (2000) build a matrix of dimensions of CEO change and "interact" forced versus voluntary exit with insider versus outsider successors. They suppose that a forced CEO exit followed by an outsider has the most disruptive character and empirically confirm for this combination a positive performance effect.

Bruton et al. (1998, 2000) survey 68 VC companies and investigate their impact towards CEO dismissal, and furthermore the firm performance reaction to this dismissal. They find that the removal of a CEO has a high impact on performance. This also confirms the expectations of the VC investors.

3.2.2.2. The relation between VC financing and firms' innovation activities

The relevant literature on the impact of VC financing on firms' innovation activities is reviewed in this section. This is the starting point for the analyses in Section 3.5. Many of the studies, investigating the link between venture capital financing and innovation, analyze the effects on the industry level. Kortum and Lerner (1998, 2000) test whether venture capital spurs innovation activity. They estimate a patent production function at the industry level for the period 1965-1992 derived from the knowledge production function introduced in Griliches (1979), and find a positive and significant effect of venture financing on firms' patenting behavior. A limitation of their result is that the reduced-form regression may overstate the VC impact since VC funding as well as patenting may be affected by the unobserved arrival of technological opportunities. Kortum and Lerner address causality concerns by using an instrumental variable approach and exploiting the fact that in the history of the US venture capital industry there has been a substantial increase in the size of funds raised by VC companies due to a policy shift in the late 1970s[14]. In a second approach, they use R&D expenditures as a control for the arrival of technological opportunities anticipated by the firms. For this purpose, they re-formulate the reduced-form regression equation

[14] The so-called "prudent man" rule of the Employee Retirement Income Security Act clarified by the Department of Labor allows pension funds to invest in venture capital.

and divide it by R&D: Conditional on the ratio of industry venture capital to industry R&D expenditures and the expected value of an innovation, the patent-R&D ratio is independent of technological opportunities. Finally, Kortum and Lerner (2000) suspect that venture capital may spur patenting while having no impact on innovation. They investigate whether VC-funding only augments the propensity to patent without stimulating innovation. Kortum and Lerner analyze this effect by comparing indicators of patent quality between VC- and non-VC-backed firms. They use patent citations (see Trajtenberg (1990)) per patent to measure the average importance of the firms' patent awards. Furthermore, they use the frequency and extent of patent litigation to investigate the importance of the patents (see Lanjouw and Schankerman (1997)). For all measures of patent quality, they find that VC-backed firms hold higher quality patents than non-VC-backed firms, i.e. VC financing has an impact on innovation. For Germany, Tykvovà (2000) confirms a positive influence of venture capital on patent applications at the industry level using a similar approach as Kortum and Lerner.

Ueda and Hirukawa (2003) criticize the interpretation of the Kortum and Lerner (1998, 2000) papers. They state that it is one-sided because the opposite causality may also exist. They argue that opportunities for firms to innovate and/or grow fast will lead to an augmented demand for venture capital, and hence, lead to the growth of the venture capital market. Ueda and Hirukawa point out that venture capital is a complementary asset for young and innovative firms, particularly, in times when significant innovations are made. This may be because with substantial innovations business opportunities arise which may trigger firm startups. Ueda and Hirukawa address the causality issue by using the growth of total factor productivity as a measure for innovation and test for Granger type causality. They find that the complementarity of innovation and venture capital investments does not only stem from the positive impact of VC investments on innovation but also from the positive impact of innovation on VC investment.

Ueda and Hirukawa (2006) extend the studies by Kortum and Lerner to the "bubble" period, i.e. the growth period of the VC industry during the late 1990s, and question whether the productivity of VC investments has been diminished during the boom. According to Lerner (2002) the impact of venture capital on innovation is not uniform and depends on the cyclicality of the VC market. For example, during boom periods the effectiveness of VC may be lower due to an overfunding within particular sectors whereas in long bust periods promising firms may remain unfunded. The period, Ueda and Hirukawa (2006) cover, consists of the years 1968 to 2001. They confirm the results of Kortum and Lerner and state that VC investments continue to be a highly effective driver of patent activities. Furthermore, they reinvestigate the findings of their 2003 paper with the extended data set, and find instead that VC investments have no significant effect on the growth of total factor productivity (TFP) but that they positively affect labor productivity growth. They associate this finding with technology substitution using more energy and material and less labor in VC-intensive industries. Ueda and Hirukawa give several explanations for their puzzling results of the positive impact of VC funding on the propensity to patent and the insignificant impact on TFP growth: First, venture capitalists prefer start-up firms as investees and these are supposed to have a higher patent propensity than established firms in order to appropriate the returns to innovation. Second, a change in the patent policy may have affected patenting and VC investment. Third, VC facilitates firm entry and may help increase the competitive pressure which, in turn, may increase the patent propensity of established firms, i.e. established firms may patent for strategic reasons since the threat of entry is strong due to the support by venture capitalists[15].

Some studies investigate the relation of VC funding and innovation at the firm level. Da Rin and Penas (2007) link venture financing and firm's absorptive capacities. They use the Dutch part of the Community Innovation Survey (CIS) and focus on combinations of R&D 'make' and 'buy' which correspond to the build-up of absorptive capacity. Their results suggest that VC financing has an impact on innovation strategies since the entry of a VC investor is associated with an increase in the combination of both strategies and in 'make' decisions, but not in 'buy' R&D activities.

Engel and Keilbach (2002) investigate the impact of VC financing on firm's growth rates in terms of employment and on innovative output. They use a nearest neighbor matching technique, and find in the first stage that VC involvement depends on pre-foundation patenting behavior. Regarding the patenting activities of VC-backed firms, they show that VC-backing has a positive effect on patent counts compared to non-VC firms.

Bretoni et al. (2006) find a highly positive effect of VC financing on firms' patenting activities for Italian new technology-based firms using a hand-collected panel data set

[15] Note that the level of analysis is the industry and not the firm. Hence, it is possible that industry patent propensity measures the reaction of established, non-VC-funded firms. For example, incumbent firms patent their innovation output to prevent firm entry, so-called preemptive patenting (see e.g. Gilbert, Newbery (1982)). And firm entry, in turn, may have been made possible due to the existence and the investment behavior of the VC industry.

of high-tech manufacturing for the years 1993 to 2003. They show that after receiving VC financing the propensity to patent increases whereas they do not detect such a high patenting propensity before the VC investment. Baum and Silverman (2004) discover no significant effect for VC spurring innovation activities of start-ups in Canadian biotechnology. On the contrary, they find that the amount of pre-IPO financing is positively affected by patents in the year before financing. Hence, their results suggest that patenting is a signal of innovative capabilities and prospective returns to investors.

Hellmann and Puri (2000) link the firm's product market strategy to the provision of venture capital analyzing a data set of Silicon Valley high-tech startups. They particularly focus on innovator and imitator strategies. They find that innovators are more likely to be financed by venture capital, and obtain the funding earlier in the life cycle than imitators. Moreover, they find that the time to market is shorter if venture capital is present in the firm, particularly if the firm follows an innovator strategy.

Timmons and Bygrave (1986) investigate the role of venture capital in financing innovation for economic growth. They study 464 VC firms and find that less than 5 % of them account for nearly 25 % of all investments in highly innovative technological ventures. Their most important result is that it is not the provided capital that fosters technological innovation but the nonmonetary, high value-added contributions of the VC companies. Those highly valuable nonmonetary contributions consist of helping to find key management-team members, providing credibility with suppliers and customers and helping to shape the business strategy.

Schwienbacher (2004) presents a model which links innovation to the stage of VC exit and claims that the prospective exit causes agency problems because the exit decision provokes uncertainty to the entrepreneur about his future control of the firm. According to Schwienbacher, the entrepreneur may favor IPO as exit route – an IPO may enable him to participate in the firm's strategy shaping as a manager or a shareholder – and he thus chooses the strategy that favors the IPO. This in turn may have an impact on the extent of innovation since in the model the strategy also includes R&D activity. Whether this leads to more or less innovation depends on the market game.

3.3. Data Set

The data set we use for the investigation of the impact of VC funding on firm decisions is the ZEW Hightech Founders Survey 2006 (ZEW-HF06). The data set is based on a telephone survey of German high-tech firms founded between 1996 and 2005. The survey has been conducted by the Centre for European Economic Research (ZEW) on behalf of Microsoft Germany and Impulse, a German entrepreneur magazine. The telephone survey was intended to bridge a gap which exists in Germany concerning the analyses of entrepreneurship. For studies in entrepreneurship, no such data set like innovation surveys, the Mannheim Innovation Survey (MIP) in Germany or the Community Innovation Survey (CIS) for the European Community, exists. The ZEW Foundation Panel, which is provided semi-annually by Creditreform, Germany's largest credit rating agency, lacks many information on crucial factors in entrepreneurial activities relevant for research on entrepreneurship, like many characteristics of the management team and strategic issues, for example the strategy for market entry. The telephone survey used for the empirical analyses was the first trigger for kicking off a panel data set on entrepreneurship, the KfW-ZEW Founders Panel, which is also intended to provide information concerning the evolution of different parameters like strategy and innovation decision. The first launch has taken place in 2008.

The ZEW-HF06 is based on a sample of the ZEW Foundation Panel (ZEW-FP). The population has been defined by foundation dates between 1996 and 2005 and by specific technology and knowledge-intensive sectors. The technology- and knowledge-intensive sectors are classified according to Grupp et al. (2000) for manufacturing, and Engel and Steil (1999) and Nerlinger (1998) for service sectors (see Table B.1 on pp. 211 in the Appendix for a list of industries and Appendix B.2 on pp. 214 for a more detailed description of the ZEW-FP and the procedure of the telephone survey).

The resulting data set is a stratified random sample. Stratification is based on foundation period and on industry clusters. Foundation periods have been clustered into two groups: founded between 1996 and 2000 and between 2001 and 2005, which represents the boom and the post-boom period in high-tech industries in Germany. Industries are classified into five groups. High-tech manufacturing is divided into three groups. First, high-tech manufacturing including all manufacturing sectors with a R&D intensity above 8 %, so called "Spitzentechnik" (named hereinafter *high-tech 1*). Second, high-tech manufacturing including all manufacturing industries with a R&D intensity between 3.5 % and 8 %, so called "Hochwertige Technik" (named hereinafter *high-tech 2*). From these two clusters, the *hardware* sectors have been taken apart as a third group of high-tech manufacturing industries. The technology-oriented service sectors have been divided into software industry and other technology-oriented services. Table B.2 in Appendix B.2 displays the population distribution according to the stratification arguments. Table B.3 shows the distribution of the surveyed firms according to the stratification arguments. The interviews have been carried out in February and March 2006. The persons interviewed are either the owner or an executive so that the respondent should have been able to adequately answer the questions. Altogether, 6,315 firms have been contacted within the pre-defined survey period of three weeks. In the end, 1,085 interviews have been completed, thus the response rate was 17 %. After some cleaning, we end up with 1,065 firms for our analyses.

Table 3.1.: Distribution of industries and cohorts in the ZEW-Hightech Founders Survey 2006

	high-tech 1	**high-tech 2**	**hardware**	**software**	**tech. serv.**	**total**
1996 to 2000	84	116	91	114	116	521
2001 to 2005	93	123	96	114	118	544
total	177	239	187	228	234	1,065

3.3.1. Including external information

As mentioned at the beginning of this section, the basis of the ZEW-HF06 is Creditreform data. By means of the identifier, other information provided by Creditreform can be merged to the survey data, like information on the credit rating index and on stakeholders (e.g. age).

For the analysis of VC involvement, we want to identify the year of VC entry and different types of VC investors. Since less than half of the VC-backed firms in the sample report the starting date of VC funding we need to use other data sources to accurately identify the year of VC entry. The approximation of the VC entry date for missing values in the ZEW-HF06 is done by merging information on corporate stakeholders from the ZEW Foundation Panel. VC companies have been identified by looking up the names of corporate stakeholders. For a substantial part of the missing dates, we could thus identify entry dates.

As presented in the literature review VCCs provide capital and at the same time management support. Hence, there may be two different reasons why the entry of a VC investor could influence firms' decision: First, the provision of funds may alleviate financial constraints. For illustration of this argument, think about innovation output. The improvement of the financial situation may enable the entrepreneur to screen more intensely technological opportunities. Second, VCCs are often actively involved in their portfolio firm, and may hence contribute to the firms' success. For example, continuing the argument of innovation output, the management support enables the firm to better screen the technological opportunities, and hence to identify the most promising ones. Consequently, the firms may be more productive in terms of innovation output because they can make use of the experience, advice and contacts of the active investor. This example can be applied to other fields of corporate decisions. We try to disentangle the effect by distinguishing different types of VC investors. The degree of involvement is supposed to vary for specific VC investor types. We distinguish private VC companies (independent VCCs, corporate VCCs and bank VCCs) and public VCCs (Mittelständische Beteiligungsgesellschaften (MBG), Technologie-Beteiligungs-Gesellschaft (tbg), state banks (Landesbanken) and savings banks (Sparkassen)). Private VCCs are expected to be more intensely involved in their portfolio firms. One reason for this more intense involvement is their return orientation which may cause private VCCs to be more actively involved than their public counterparts. Furthermore as pointed out in Section 3.2.2, the active involvement via management support is one means to reduce information asymmetries in the context of young firms active in highly risky environments. Public VCCs are assumed to promote industries, regions and/or employment growth. Usually, they are assumed to have a broader investment focus and to be less experienced regarding industry specificities than private VC companies (Leleux, Surlemont (2003), Lerner (2002)). Hence, their contribution to management support is supposed to be small.

In order to classify the VC investors, we merge the corporate stakeholder information incorporated in the ZEW-FP to the data set. Unfortunately, we are only able to identify the type for about 75 % of the firms indicating in the ZEW-HF06 that they are VC-backed. This may be surprising, but remember that VCCs often choose convertible securities as the adequate financing instrument. These instruments have a debt character at the beginning and may then be transformed to equity. Moreover, we could only identify 11 public VCCs' investments. Particularly, public VC investors choose to contract as silent partner. In both cases, Creditreform will have difficulties in investigating those corporate stakeholders. Since we only identify few public VCCs, we have decided to renounce presenting results for their involvement.

Slightly more than half of the VC investors could be classified to be private VCCs. For about 25 % of VC investments, the type of VC investor cannot be assigned, and consequently it is not clear whether those VC investors are private or public VCCs. Therefore, the estimation including the private VC dummy can only serve as a sort of robustness check. This check tests whether the effect of VC financing can be assigned to the active involvement by comparing the effects of all VC investors to the effect of the subgroup of private VCCs: If we find a significantly higher effect of public VC financing with respect to the average VC effect, this could be a hint that the active involvement is an important impact factor. Thus, assuming that the main difference between VC investor types is the degree of involvement and industry experience the difference of the effects of the average VC investor, deduced by the effect for all VC investors, and private VC investors is interpreted as the value-added assigned to the management involvement. If we find no significant difference this does not mean that there is no additional effect which can be assigned to the management support because the "non-identified" group of VC investors, i.e. all VC investors to which we cannot definitely match a VC type, may be heterogeneous in the sense that it may also include VCCs which would be classified as private VCCs.

External sources, like Patent data, are included by making use the so-called *search engine* developed by Thorsten Doherr. First, a search list, i.e. the names of the firms included in the ZEW-HF06, is built. Usually, the firm names consist of several words which are searched within the external data set. The search engine constructs an "identity number" which indicates the percentage of similarity between the name in the search list and the one in the external data set. The percentage is an "inverse-frequency-weighted" percentage, i.e. words which frequently occur (like the legal form appendage GmbH) are assigned a very low "number", and hence, a lower contribution to the similarity percentage. The result of the search engine is the result list, a list of similar firms and the corresponding similarity percentage. The result list needs to be hand-checked in order to identify identical firms in the data set. Address information may facilitate the finding of the closest "twin"[16].

3.3.2. A first look at the data

For the ZEW-HF06 survey, manifold information was asked. The first part deals with the entrepreneur or entrepreneurial team. Information is gathered on the educational background concerning degrees and foci (e.g. predominantly technical), previous and contemporaneous employments in firms or universities or entrepreneurial background. The second group of questions centers on the characteristics of the most important product with respect to sales. The nature of the product has been asked for, like physical product versus service or intermediate product and the scaling of the production process as short- or long-term. Finally, information about the firm has been asked like the number of employees, R&D activities and the use of own patents.

Table 3.2 shortly summarizes the description of some key variables, and Table 3.3 displays some key descriptive statistics to characterize the average firm included in the data set. The average firm has about 4.4 employees in the first year of existence (*initial size*) and 11 in the year 2005 (*size*). The average founding team consists of two executives (*number team*). About 56 % of the firms are involved in R&D either permanently or occasionally (*R&D*), and over 33 % continuously carry out R&D activities (*cont. R&D*). Over 11 % of the firms use *patent*s filed by the company or the entrepreneur, and 4 % use patents which have been filed before foundation (*patent_before*). It may seem awkward that almost half of the firms are not engaged in R&D and almost 90 % do not use own patents. This may point at several firms which are not innovative although they are supposed to operate in high-tech industries. This finding may be due to the fact that before kicking off the telephone survey we were only able to use an industry-based definition of high-tech sectors to identify high-tech firms so that some firms, which are assigned to these sectors, may not be innovative. Moreover, we also cover knowledge-intensive services which may have difficulties in patenting.

[16] The process gets even more complicated since including address information will necessitate a weighing of name and address information according to its contribution to truly identify a match, i.e. the firm name is given the highest percentage (about 70 %), the ZIP Code, the street name and the city have lower percentages.

Table 3.2.: Description of selected variables in ZEW-HF06

Variable name	**Type**	**Description**
venture capital	indicator	VC financing
initial size	continuous	number of employees at firm foundation
size	continuous	number of employees in year 2005
number team	continuous	number of top managers at firm foundation
R&D	indicator	R&D activities
R&D-cont	indicator	continuous R&D activities
patent	indicator	patent application
patent_before	indicator	patent application before firm foundation
m_graduate	indicator	PhD or university degree: highest degree in founding team
m_technical	indicator	highest degree in founding team: predominantly technical
m_indexp	indicator	at least one manager has industry experience as employee and/or entrepreneur
m_majority	indicator	top management held majority stake at foundation
good rating	indicator	good initial rating
medium rating	indicator	medium initial rating
intermediate	indicator	intermediate product
East Germany	indicator	firm location in East Germany

Regarding the initial management team, Table 3.3 shows that 64 % of the firms have a founding team with at least one member having an academic background (*m_graduate*), almost 60 % of the highest degrees in the founding team are predominantly technical (*m_technical*) and 76 % have at least one manager with industry experience either as an employee or as an entrepreneur (*m_indexp*). In 28 % of the firms, the founding management team held majority stake, i.e. there is no separation of ownership and control. About 30 % of the firms had a good initial rating and over half of them a medium one[17].

Table 3.3.: Descriptive statistics for selected variables in the ZEW-HF06

	Mean	**Std. Dev.**	**Min**	**Max**
venture capital	0.075	0.264	0	1
initial size	4.389	5.084	0.5	40
size	11.147	18.295	0	320
number team	2.048	1.216	1	6
R&D	0.557	0.497	0	1
cont. R&D	0.336	0.472	0	1
patent	0.116	0.321	0	1
patent_ before	0.042	0.201	0	1
m_ graduate	0.638	0.481	0	1
m_ technical	0.598	0.491	0	1
m_ indexp	0.759	0.428	0	1
m_ majority	0.275	0.447	0	1
good rating	0.292	0.455	0	1
medium rating	0.568	0.496	0	1
intermediate	0.405	0.491	0	1
East Germany	0.160	0.367	0	1
Number of observations		876		

Since this chapter predominantly deals with venture capital financing, the next table depicts the results of a probit estimation in order to identify the firm characteristics which influence the probability of receiving VC funding. Table 3.4 shows the marginal effects calculated at the sample means.

The results show that VCCs' decision to invest in high-tech entrepreneurial firms is based on some characteristics of the founding management team. Firms with larger

[17] The rating indicators are based on the rating index provided by Creditreform, which is grounded on some firm characteristics. The index ranges from 1 to 5, whereas 1 is the best and 5 the worst rating. Since the rating index is not a metric variable, we include two indicator variables. Czarnitzki and Kraft (2007) state that Creditreform clusters the rating index in classes, e.g. "good" ranges from 1.3 to 2 and "average" from 2 to 3. Since the best initial rating in the sample is 1.93 we decided to adjust the indicators. *Good rating* is defined as a rating index between 1.9 and 2.5 and *medium rating* ranges from 2.5 to 3.5.

Table 3.4.: Marginal effects for probability of VC-funding (probit estimation)

	Marg.Eff.	(Std.Err.)
log(initial size)	0.006	(0.008)
log(number team)	0.030**	(0.015)
cont. R&D	0.032*	(0.017)
patent_before	0.156**	(0.074)
m_graduate	0.048***	(0.014)
m_technical	0.006	(0.013)
m_indexp	0.013	(0.014)
m_majority	-0.024	(0.014)
good rating	0.027	(0.027)
medium rating	0.018	(0.019)
intermediate	0.023	(0.015)
East Germany	0.022	(0.021)
industry dummies	*included*	
foundation years	*included*	
log Likelihood	-196.21	
χ^2 *(all)* [a]	75.81***	
χ^2 *(industries)* [b]	7.04	
χ^2 *(foundation years)* [b]	10.22	
McFadden's R^2	0.162	
McFadden's adjusted R^2	0.064	
Cragg-Uhler's R^2	0.200	
BIC	-5,386.98	
Number of observations	876	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the marginal effects of a probit model which are calculated at the sample means. Marginal effects of dummy variables are interpreted as discrete change from 0 to 1. Standard errors are transformed by the delta method.
[a] χ^2(all) displays a test of the joint significance of all variables.
[b] χ^2(industries) and χ^2(foundation years) display tests on the joint significance of industry and foundation year dummies.

teams have a higher probability to receive VC funds than firms with smaller teams. Larger teams may more likely embody a larger portfolio of skills and abilities than smaller teams (see Lazear (2004)). Furthermore, if in the initial team at least one member with academic background is present, this also increases the propensity of VCCs to invest. These effects reflect the conjectured investment behavior: VC companies usually take a closer look at the management team and obviously prefer larger teams and team with academic background. The preference for entrepreneurial teams with academic background may be due to the fact that novel products incorporating cutting-edge technologies may mainly be developed by persons who have access to academic research.

Finally, firms which continuously carry out R&D activities and/or use patents filed before firm foundation are more likely to get VC financing. This perfectly fits the criteria which are assumed to guide the VCCs' investment behavior: On the one hand, they prefer risky investments with a high expected return. R&D-intensive firms are supposed to be risky because the R&D process is highly uncertain, but if the process is successful the returns may be large. On the other hand, they usually ask firms to prove the quality of their business strategy. Patents may be regarded as one means to show the feasibility of the project(s), and hence to reduce information asymmetry.

3.4. Venture Capital, Executive Turnover and Firm Performance

This section is based on the literature presented in Section 3.2.2.1, and investigates the effect of VC financing, respectively the involvement of a VC investor, on the turnover of founding executives. In a second step, the determinants of the time span between firm foundation and the first change in the executive team are analyzed. Since executive turnover is usually motivated by a bad firm performance, turnover should then lead to superior performance. Therefore, we show the effects of changes and VC involvement on firm performance.

3.4.1. Hypotheses

Besides supplying capital to firms, VC companies also provide value-added services like management advice and support. Furthermore, they typically have extensive contractual control rights contingent on the extent of asymmetric information and agency problems (Kaplan, Strömberg (2004)) which enable them to actively intervene in the management of their portfolio companies. Such potential activity is motivated by profit generation, the main aim of VC investors. As stated in Section 3.2, active involvement is an efficient means to reduce information asymmetries in small firms operating in a highly risky environment. One of the strongest ways, in which VC investors may intervene, is a structural change within the executive team. Assuming that founders have strong personal ties to their firm and provide crucial knowledge, founding teams may be reluctant to changing the top management.

As opposed to most of the literature, which concentrates on changes in the position of the CEO, this section looks at the developments within the entire top management. Furthermore, a deeper look at the kind of changes within the founding team is taken. We distinguish between replacement of one or more executives, enlargement and reduction of the team. If the team needs additional know-how, replacement or enlargement are expected to take place. If the firm wants to expand into additional business segments, the executive team may be enlarged whereas in the case of too large and inefficient initial teams, it may shrink.

The first part of the section analyzes whether changes in the founding team are more likely in firms obtaining venture capital. Furthermore, since initial founders are assumed to be reluctant towards changing the top management team, and VC investors may be more "impatient", transformations of the initial executive team should occur earlier if the firm is VC-backed. This conjecture is based on the findings of Hellmann and Puri (2002) who find that VC-backed firms experience replacement of the founder more probably and faster.

Hypothesis 1: *Venture capital financing increases the likelihood that the initial top management team will change.*

Hypothesis 2: *The time until first change is shorter if the firm is VC-backed.*

Furthermore, turnover of top managers is assumed to be intended to improve performance since bad performance is often the reason why turnover is forced to happen. Additionally in young high-tech firms, after the first years of existence the challenges for the executive team may change substantially, e.g. when the firms have trespassed the product development stage and arrive at the so-called expansion stage which is characterized by the buildup of production and product sales. This new accentuation makes a change sometimes necessary to ensure that the firm is more successful. Therefore, we conjecture that changes in the executive team have an impact on firm performance.

Hypothesis 3: *Changes in the original management team have a positive impact on firm performance.*

Finally, VC-induced change should have an impact. VC companies are return oriented, and therefore intervene whenever they have the impression that businesses could be run better. Therefore, VC companies may push for a change in the top management, and thus, induce a better performance. Bruton et al. (1998, 2000) provide evidence on this issue.

There is also a number of studies dealing with the impact of VC funding on firm performance whereas firm performance is often considered after the IPO. Davila et al. (2003) propose some rationales why VC financing should influence firm growth positively. Before investing funds, the potential investee firms need to pass a tough screening and due diligence process, which should enable VC companies to pick the winners (Zacharakis, Meyer (1998, 2000)). Furthermore, they provide value added activities like management support, networks and contacts which could benefit the firm.

Hypothesis 4: *VC involvement and VC-induced changes of the original management team positively influence firm performance.*

3.4.2. Variable definition and descriptive statistics

The empirical analysis is divided into three parts. The first investigates the impact of VC financing on the probability of executive turnover. The second shows evidence about the timing of changes in the initial executive team, and the third part tests the effects of changes (whether VC-induced or not) and VC financing on firm performance. The underlying data set is the ZEW-HF06 described in Section 3.3, i.e. we use a cross-section data basis.

Executive turnover is represented by three different categories: replacement, enlargement and reduction. In order to represent these changes, we merge information concerning individual stakeholders taken from the ZEW Foundation Panel (ZEW-FP). To describe the executive team we only keep those stakeholders who are recorded as owner (Inhaber), CEO (Geschäftsführer), general partner (Komplementär) or member of the executive board (Vorstand). The notions as such give rise to concerns as to their executive function, e.g. an owner does not necessarily manage the firm. Investigations of the stakeholder variable revealed that only one category is present for each firm-year and the category "owner" only arise in very small firms, so that we assume that stakeholders classified as owners also manage the firm.

The three categories of change are defined by comparing the executive team in one year with the top management team in the next year[18]. Replacement is defined as at least one top manager left and at least one "new" executive joined the team. Enlargement signifies that the original executive team remains unchanged, and at least one additional executive enters the team, and reduction measures that at least one member left the founding executive team leaving the remaining team unchanged.

[18] Concerns may arise about the speed of information updates by Creditreform, e.g. when it comes to reporting a change in the executive team. Heger and Tykovà (2007) contacted a randomly chosen sample of 50 firms from the ZEW-FP in order to obtain information on the executive team. The result was that all but one of the recent changes in the team of executives had been registered by Creditreform within the following six months.

The information of the ZEW-FP provides stakeholder information over time, so that, by comparing the members of the executive team in the single years, we are able to determine the year of change in the top management. This is important when we want to identify previous VC investment. For the analyses of the probability of change occurrence (Section 3.4.3.1) and of the impact of changes (Section 3.4.3.3), we use cross-section information. As regards the investigation of the timing of change, discussed in Section 3.4.3.2, we expand the data set to represent firm-year observations until the first change occurs. This is needed to accurately estimate duration models. Most exogenous variables depict firm or top management characteristics which are unchanged, e.g. because they are measured at firm foundation. The only observed variable which changes between firm foundation and first change is the status of VC financing.

First, we explain the variables included in the analyses of first change, both the probability and timing of first change. The descriptive statistics in Table 3.6 show that 31 % of the firms in the sample experience a change in the executive team. In almost 14 % of the firms, at least parts of the original executive team have been replaced, about 10 % of the firms have experienced an enlargement, and more than 7 % a reduction of the original executive team.

For the analyses of the probability and timing of executive turnover, we need to identify whether VC funding took place previous to the occurrence of first change to the top management team. Since neither the exact date of change nor of VC funding is known, we relate VC involvement in the previous years[19] to changes in the executive team. Thus, the VC variables reflect that the involvement has at least existed in the period previous to the year in which we observe a change. Whenever the timing of VC financing was unclear, the identification of the investment year was done according to the procedure described in Section 3.3.1. Almost 6 % of the firms in the sample receive VC financing previous to first change.

Since VC investors are largely heterogenous, e.g. with respect to management support and active involvement, we test for this issue by including the private VC dummy. The distinction of private VC investors is done by merging the corporate stakeholder variable provided by the ZEW-FP and by classifying the types as described in Section 3.3.1.

[19] The VC investors observed in the sample were still active at the end of the observation period, i.e. they still held a certain amount of stake. There were only two exceptions, for which the divestment occurred after the first change, and we account for this issue.

Table 3.5.: Variables description for changes in the top management

Variable name	Type	Description
Dependent variables		
first change	categorical	change within the initial top management team including the categories replacement, enlargement, reduction and no change
time to change	integer	time that elapses until first change in top management team
time to replacement	integer	time that elapses until first replacement in top management team
time to enlargement	integer	time that elapses until first enlargement in top management team
time to reduction	integer	time that elapses until first reduction in top management team
Explanatory variables		
venture capital [a]	indicator	venture capital financing in previous years
private vc [b]	indicator	private VCC financing in previous years
number team	integer	number of executive team members at foundation
initial size	continuous	logarithm of number of employees at foundation excluding top managers
m_graduate	indicator	PhD or university degree: highest degree in founding team
m_technical	indicator	highest degree in founding team: predominantly technical
m_above55	indicator	at least one member was minimum 55 years old at foundation
m_indexp	indicator	at least one manager has industry experience as employee and/or entrepreneur
m_majority	indicator	top management held majority stake at foundation
good rating	indicator	good initial rating
medium rating	indicator	medium initial rating
cont. R&D	indicator	continuous R&D activities
East Germany	indicator	firm location in East Germany
industry dummies	indicators	5 industry dummies according to stratification argument
foundation year	indicators	6 foundation year dummies

[a] *venture capital* displays that a VCC was involved in the year previous to change or before.

[b] *private vc* displays that a VCC was involved in the year previous to change or before.

Other variables that may impact on changes in the top management team are its characteristics, or more precisely, the characteristics of its members. Bruton et al. (2000) find that the main reasons for dismissal are the CEOs' abilities. Since we look at the first change, characteristics of the founding teams are taken. Variables that account for the top management are indicated with a leading *m_*.

First, we control for the educational and working background of the original executive team. Jain and Tabak (2008) examine the determinants of the likelihood that the founder CEO remains CEO at the IPO, and find that career experience in product R&D has a positive influence compared to other functional tracks and founder's age has a negative one which suggests that risk aversion and proneness to effort matter. Furthermore, they find that the size of the founding team has a positive impact on the persistence of the founder CEO at IPO. Jain and Tabak's explanation is that founding teams are structured such that they provide different and complementary skills and experiences (see also Lazear (2004), Wasserman (2003)). The variable *m_graduate* reflects that the highest educational degree attained by at least one member of the founding team is a university or a PhD degree, whereas *m_technical* controls for whether the highest degree is predominantly technical. Finally, we include an indicator whether the firm performs continuously R&D (*cont. R&D*) which is the case for 37 % of the firms.

Moreover, work experience may be a crucial characteristic of the executive team since according to the human capital theory (see e.g. Becker (1964), Carroll, Mosakowski (1987), Dobrev, Barnett (1999)) work experience results in skills which are not easily learned by other means. To reflect the working background either gathered in a company or by previous entrepreneurial activity by at least one member of the founding team, a dummy taking unit value if at least one has got relevant industry experience (*m_indexp*) is inserted.

Barro and Barro (1990) state that the turnover of bank CEOs depends on the age of the CEO. They find that the probability of replacement decreases until the age of 52 and then rises again. They suggest that this is due to the approaching of the legal retirement age. In order to control for the age of the team members, a dummy variable is included which takes unit value when at least one of the team members has already reached the age of 55 at the foundation date (*m_above55*). This variable is also intended to capture voluntary exits of top managers. Clearly, there may also be other reasons for voluntary exits like the emergence of new career opportunities, but unfortunately, we are not able to control for them. Over 14 % of the firms are founded by a team in which at least one above-55-year-old person participated.

Table 3.6.: Descriptive statistics for estimation of executives replacement

Variable	Mean	Std.Dev.	Min	Max
Dependent variables				
first change	0.311	0.463	0	1
first replacement	0.137	0.344	0	1
first enlargement	0.099	0.299	0	1
first reduction	0.075	0.263	0	1
time to change	2.813	1.897	0	9
time to replacement	2.757	1.895	0	9
time to enlargement	2.708	1.907	0	8
time to reduction	3.063	1.890	0	8
Explanatory variables				
venture capital [a]	0.057	0.233	0	1
private vc [b]	0.033	0.179	0	1
number team	2.046	1.214	1	6
initial size	4.347	4.854	0.5	38
m_ graduate	0.639	0.481	0	1
m_ technical	0.595	0.491	0	1
m_ indexp	0.761	0.426	0	1
m_ above55	0.109	0.312	0	1
m_ majority	0.281	0.450	0	1
good rating	0.289	0.454	0	1
medium rating	0.575	0.495	0	1
cont. R&D	0.337	0.369	0	1
East Germany	0.163	0.369	0	1
Number of observations		855		

[a] *venture capital* displays that a VCC was involved in the year previous to change or before.

[b] *private vc* displays that a VCC was involved in the year previous to change or before.

Furthermore, larger founding teams increase the bargaining power of the founding executives and provide a larger amount of potential individuals for the CEO position. Jain and Tabak (2008) show that the probability that founder CEOs are still in charge at the IPO is lower for independent boards proxied by larger outside director presence and higher top management team ownership. Applying this finding to high-tech entrepreneurs, we include the number of team members (*number team*). Furthermore, we control whether the founding executives held majority stake at firm foundation. CEO turnover is more sensitive to performance when the board is more independent (Hermalin, Weisbach (1998)), i.e. if top managers hold the majority stake changes should be less likely because they are reluctant to dismiss themselves[20]. We use a dummy variable indicating whether the executive team holds the majority stake (*m_ majority*) at firm foundation. Jain and Tabak (2008) use a similar measure.

Moreover, we control for some firm characteristics. The number of employees is supposed to have an impact: The higher their number, the more differentiated, complex and challenging communications, coordination and functions within the firm get (Greiner (1972)). Hence, larger firms (*initial size*) should have a higher probability for executive turnover, particularly for replacement and enlargement.

Furthermore, we include the two indicators reflecting whether the initial rating index was good (*good rating*) or medium (*medium rating*)[21]. These are intended to measure business risk and access to debt financing. Finally, geographic (*East Germany*) and foundation year dummies are included as well as industry dummies. Industry dummies should reflect the characteristics of the sector. The ability of the CEO to influence firm performance, and hence, his likelihood to get dismissed varies by market factors (Porter (1980)) which differ across segments, stage of industry development and size of the primary pool of potential executives (Wasserman et al. (2001), Fredrickson et al. (1988)).

The third part of the analysis tries to answer whether changes within the executive team result in a better firm performance. Our performance measures are *labor productivity*, i.e. sales per employee, and firm *growth* in terms of employees. Unfortunately, we are not able to use conventional performance measures like return on sales, return on assets, return on equity or the price-cost margin because these measures are not represented neither in the ZEW-HF06 nor in the ZEW-FP. Particularly for entrepreneurial firms, growth is often viewed as a proxy for companies' success and is frequently used in research on entrepreneurship (see e.g. Davila et al. (2003)). Furthermore, a VC investor is interested in the market value at the time of exit. If the exit route is an IPO the

[20] See also Fredrickson et al. (1988) and Rubenson and Gupta (1992).
[21] For the definition of the rating indicators refer to Section 3.3.2.

Table 3.7.: Variables description for performance issues

Variable name	Type	Description
Dependent variables		
growth [a]	continuous	growth in number of employees (excluding top managers)
Δ *labor productivity*	continuous	difference between last and first sales per employee in million Euro
Explanatory variables		
venture capital [b]	indicator	previous VC financing
private vc [b]	indicator	previous private VC financing
replacement [b]	indicator	previous replacement within top management team
enlargement [b]	indicator	at least one new member joint the original team previously
reduction [b]	indicator	at least one member left the original team previously
number replacement [c]	continuous	number of previous replacements from firm foundation to current period
number enlargement [c]	integer	number of previous enlargements from firm foundation to current period
number reduction [c]	integer	number of previous reductions from firm foundation to current period
number team	integer	number of executive team members at foundation
m_graduate	indicator	PhD or university degree: highest degree in founding team
m_technical	indicator	highest degree in founding team: predominantly technical
m_indexp	indicator	one manager has industry experience as employee and/or entrepreneur
m_majority	indicator	top management held majority stake at foundation
m_above55	indicator	one member was minimum 55 years old at foundation
good rating	continuous	good initial rating
medium rating	continuous	medium initial rating
cont R&D	indicator	continuous R&D activities
firm age	continuous	years since firm foundation
East Germany	indicator	firm location in East Germany
industry dummies	indicators	5 industry dummies according to stratification argument
log(initial size)	continuous	logarithm of number of employees excluding top managers at firm foundation (only in growth equation)
$log(labor\ productivity_0)$	continuous	lagged logarithm of labor productivity (only in labor productivity equation)

[a] Growth is measured in terms of exponential employment growth between two subsequent periods (log(number of employees (t)) - log(number of employees (t-1))).

[b] Those variables indicate that the event occurred in the year previous to the observation period of the performance measure or before.

[c] Those variables indicate the sum of how often the events occurred in the years previous to the observation of the performance measure.

market value can be determined. If another exit route is chosen or if the VC investor is still active in the firm (as it is mostly the case in the ZEW-HF06) this market value is unobservable. Hence, growth and labor productivity are used as proxies for the market value, assuming that those variables depict a similar figure than the market value.

Two measures are investigated in order to account for the heterogeneity of newly created firms: Labor productivity reflects firm success if a firm was able to generate sales. Many of the firms in the sample were able to generate sales within a short period of time. But other firms show a longer time pattern until first sales, partly up to 10 years. Those firms may nevertheless be successful in the long-run. Risk-taking investors often try to estimate the potential success of a firm by looking at the growth figure if sales have not yet been generated.

Performance measures are constructed by using information of the ZEW Foundation Panel about sales and the number of employees for the year subsequent to the survey year. Firm growth is calculated as exponential growth rate[22] and reflects short-term growth. The number of employees has been adjusted by subtracting the number of top managers. This correction is needed because changes in the top management would otherwise automatically result in changes of firm growth without actually changing the number of employees. For the definition of labor productivity, we take the number of employees including the top management because in this context we want to measure the contribution of all employees.

A strong test of the impact of executive turnover on firm performance would be to look at the differences in performance, i.e. to estimate whether the performance before and after the occurrence of change(s) is different. Particularly for the growth figure, this would pose a problem. For the calculation of a growth rate, two points of observations are needed. For the construction of the difference in growth rates four observations are mandatory plus at least an additional point in time at which the change in the management team took place, i.e. we would need at least five observations. Since firms in the data set are all young (median age is 5), we are not able to calculate the differences in growth rates without a substantial loss of observations. Furthermore, some firms experience change before their third year of existence. For those firms the

[22] Firm growth is defined as log(number of employees (t)) - log(number of employees (t-1)). The advantage of this measure compared to linear growth rates is that nonlinearities are avoided which would arise in the case of normalization. A disadvantage is that large growth rates would be disproportionally emphasized. Since we contemplate the growth rates in two subsequent years this should be a minor problem.

calculation of pre-change growth is not possible. Therefore, the level of growth after the period of observation of the ZEW-HF06 is investigated. For labor productivity, we only need two observations to build the differences. Therefore, in this case we estimate the differences in labor productivity by relating the first and the last observation.

As explanatory variables all kind of changes, VC financing and interaction terms of changes and VC financing are included in various combinations. Interaction terms of change and VC financing reflect whether VC-financing occurred previous to change in order to reflect possible VC-induced changes. Furthermore, the number of changes which a firm has experienced are taken into account in alternative estimations. A higher number is associated with a larger discontent as concerns the top management and may result in a negative impact on firm performance.

To reflect specificities about the management team, which are supposed to crucially influence firm performance, we rely on the information at the foundation date. First, management teams are supposed to influence firm performance, or more precisely performance is often used as an indicator to assess management abilities. Furthermore, the founding team is supposed to be decisive regarding the strategy and the business idea, and hence to substantially influence firm performance in the first years after firm start-up. Additionally, it will take some time until the new management team will be able to leave its mark if it comes to replacement or enlargement (Khurana, Nohria (2000)). Hence, we include the number of founding top managers, majority stake of the team and its educational background – whether the highest degree is academic and/or technical – at firm foundation in order to reflect the abilities of the initial management team. Moreover, we control for the fact whether one of the members of the founding top management was already 55 years old. Assuming that founders play a substantial role for performance, the participation of an older member in the founding team may also proxy the experience of the team.

We account for the starting level of the performance measures. Therefore, we include the initial size[23] in the growth equation (*log(initial size)*) and the first labor productivity ($log(labor\ productivity_0)$) in the second estimation. Those variables should account for the heterogeneity of the entrepreneurial firms, and particularly the latter should control for the effect of other variables which cannot be included because they are unobserved. Furthermore, we include some firm characteristics. *Good rating* and *medium rating*

[23]The initial firm size is also corrected for the number of managers as firm growth.

Table 3.8.: Descriptive statistics for executive turnover and firm performance

Variable	Mean	Std.Dev.	Min	Max
growth [a]	0.125	0.354	-1.099	1.792
Δ *log(labor productivity)* [b]	-0.077	1.041	-3.627	4.914
Explanatory variables				
venture capital [c]	0.092	0.289	0	1
private vc [c]	0.056	0.230	0	1
replacement [c]	0.160	0.367	0	1
enlargement [c]	0.184	0.388	0	1
reduction [c]	0.150	0.357	0	1
number replacement [d]	0.204	0.515	0	3
number enlargement [d]	0.202	0.446	0	2
number reduction [d]	0.170	0.427	0	2
log(number team)	0.626	0.563	0	1.792
m_ graduate	0.672	0.470	0	1
m_ technical	0.600	0.490	0	1
m_ indexp	0.803	0.398	0	1
m_ majority	0.276	0.447	0	1
good rating	0.279	0.449	0	1
medium rating	0.602	0.490	0	1
cont R&D	0.386	0.487	0	1
firm age	5.299	2.054	1	10
East Germany	0.190	0.393	0	1
log(initial size)	-0.327	1.839	-2.303	3.714
$log(laborproductivity_0)$	-1.657	0.731	-5.011	1.348
Number of observations		588		

[a] Growth is measured as log(employees(t)) - log(employees(t-1)).

[b] Δ labor productivity is the difference in log(labor productivity) between the last and the first period of observation.

[c] Those variables display that the event occurred in the year previous to observation of the performance measurement or before.

[d] Those variables sum the number of events occurred in the years previous to observation of the performance measure.

reflect the riskiness of the firm at firm foundation. These variables should reflect the initial riskiness of the firm. Furthermore, the rating index does not alter much over time, particularly in the short-term. Another source of firms' riskiness is whether it performs *R&D* activities. Finally, industry dummies and the East Germany indicator are included as well.

3.4.3. Research strategies and empirical results

3.4.3.1. Impact of VC investors on changes in founding teams

Since the variable change incorporates replacement, enlargement, reduction and no change as exclusive categories, we estimate a multinomial logit model. The standard starting point for discrete choice models usually is the latent regression

$$y^* = x'\beta + \epsilon \quad \text{and } y^* \text{ is unobserved.}$$

We only observe the discrete variable y consisting of four categories. Greene (2003) states that this methodology enables the representation of a set of probabilities for $J+1$ choices which depend on individual firm characteristics x_i. Normalizing β_0 to 0 for identification reasons, the following probabilities are obtained

$$Prob(Y_i = j|x_i) = \frac{e^{\beta_j' x_i}}{1 + \sum_{k=1}^{J} e^{\beta_k' x_i}} \text{ for j=1,2,3, } \beta_0 = 0.$$

The results of the multinomial logit are interpreted as odd ratios due to the normalization.

An important property of the multinomial logit is the so-called independence from irrelevant alternatives (IIA) assumption, i.e. the independence of the odd ratios of the other alternatives. This condition derives from the assumption that the disturbances are independent and homoscedastic. Hausman and McFadden (1984) state that if the IIA holds, the exclusion of one choice equation from the estimation will not change the estimates. If the remaining odd ratios are not independent from these alternatives, the estimates will be inconsistent. In the Hausman specification test,

$$HT = (\hat{\beta}_s - \hat{\beta}_f)'[\hat{V}_s - \hat{V}_f]^{-1}(\hat{\beta}_s - \hat{\beta}_f) \sim \chi^2,$$

s indicates estimates based on the restricted subset and f is based on the full set of choices. If the Hausman specification test rejects the IIA, an alternative and computationally more demanding estimation procedure has to be chosen, like the multinomial probit. The results of the Hausman test in this analysis yields, that the difference in coefficients between the full and the restricted set of choices is not systematic, i.e. the IIA holds.

Table 3.9 displays the marginal effects of the multinomial logit calculated at the sample means. Venture capital financing has a positive and significant effect on the probability of replacement compared to no changes in the original executive team. The probability will be 12.2 percentage points higher if a firm is VC-backed. This finding confirms hypothesis 1. As a robustness check, the same regression is run including a dummy variable for the subgroup of private VCCs (see Section 3.3.1 for discussion) since they are assumed to be more actively involved in the management. Private VC funding also yields a positive effect to replacement with respect to no change; the probability is 18.6 percentage points higher. The difference between the effects is significant at the 10 % level, i.e. active VC involvement seems to result in a higher probability of first replacement. Hence, private VCCs who are presumably more involved in their portfolio firms, have a higher probability to push for replacement than the average VCC.

Initially larger firms have a positive impact on replacement with respect to no changes in the founding top management. Replacing top managers may be necessary if the firm is larger and may necessitate more complex structures. Some management characteristics also play a crucial role for changes in the original executive team. The number of team members has a positive effect on the probabilities of replacement and reduction with respect to no changes in the executive team which is quite an intuitive result: The larger the team the higher the possibility of distress and thus of replacement or reduction. Moreover, industry experience in the management team increases the probability of replacement with respect to no changes. At first sight, this finding seems to be counter-intuitive. But for all variables indicating that at least one member of the top management shows this specific characteristic, the effect is a little bit more complicated to interpret: It is not necessarily the one manager with the industry experience who is replaced. It is possible that the executive with industry experience may assess

Table 3.9.: Multinomial logit for the probability of change in the initial executive team

	Replacement	Enlargement	Reduction
	Marg.Eff. (Std.Err.)	**Marg.Eff. (Std.Err.)**	**Marg.Eff. (Std.Err.)**
venture capital [a]	0.122**	0.015	-0.032
	(0.062)	(0.045)	(0.020)
log(number team)	0.055***	0.027*	0.077***
	(0.022)	(0.022)	(0.015)
log(initial size)	0.044***	0.018	0.009
	(0.013)	(0.014)	(0.010)
m_ graduate	0.037	0.017	0.016
	(0.024)	(0.023)	(0.016)
m_ technical	-0.001	-0.021	0.006
	(0.021)	(0.021)	(0.015)
m_ indexp	0.061***	0.023	-0.008
	(0.020)	(0.022)	(0.018)
m_ above55	0.177***	-0.027	-0.010
	(0.055)	(0.031)	(0.023)
m_ majority	-0.047**	-0.009	-0.015
	(0.022)	(0.023)	(0.017)
good rating	-0.055**	0.045	-0.001
	(0.027)	(0.047)	(0.027)
medium rating	-0.039	0.064*	0.018
	(0.030)	(0.033)	(0.023)
cont. R&D	-0.003	0.046*	-0.027*
	(0.021)	(0.024)	(0.014)
East Germany	-0.012	-0.010	-0.023
	(0.024)	(0.026)	(0.016)
industry dummies	*included*	*included*	*included*
time dummies	*included*	*included*	*included*
log likelihood		-709.72	
χ^2 *(all)* [b]		209.22***	
χ^2 *(industries)* [c]		11.64	
χ^2 *(foundation years)* [c]		25.00	
McFadden's R^2		0.128	
McFadden's adjusted R^2		0.044	
Cragg-Uhler's R^2		0.255	
BIC		-3,886.93	
number of observations		855	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the marginal effects of a multinomial logit model with *no change* as base category. Marginal effects are calculated at the sample means. Marginal effects of dummy variables are interpreted as discrete change from 0 to 1. Standard errors are transformed by the delta method. The dependent variable has the following categories: *first replacement*, *first enlargement* and *first reduction*. The Hausman test confirms that the IIA holds.

[a] VC variable shows whether there has been VC financing in the period(s) previous to the period of change.

[b] χ^2(all) displays a test of the joint significance of all variables.

[c] χ^2(industries) and χ^2(foundation years) display χ^2-tests of the joint significance of industry and foundation year dummies. Four industry dummies for high-tech 1, high-tech 2, hardware and software are included.

Table 3.10.: Multinomial logit for the probability of change in the initial executive team (private VC financing)

	Replacement	Enlargement	Reduction
	Marg.Eff. (Std.Err.)	**Marg.Eff. (Std.Err.)**	**Marg.Eff. (Std.Err.)**
private vc [a]	0.186*	0.022	-0.032
	(0.097)	(0.051)	(0.027)
log(number team)	0.055**	0.027	0.077***
	(0.022)	(0.022)	(0.015)
log(initial size)	0.044***	0.018	0.009
	(0.013)	(0.014)	(0.010)
m_ graduate	0.037	0.018	0.015
	(0.024)	(0.023)	(0.017)
m_ technical	-0.000	-0.021	0.006
	(0.021)	(0.021)	(0.015)
m_ indexp	0.062***	0.023	-0.008
	(0.020)	(0.022)	(0.018)
m_ above55	0.174***	-0.027	-0.010
	(0.055)	(0.031)	(0.023)
m_ majority	-0.046**	-0.010	-0.015
	(0.022)	(0.023)	(0.017)
good rating	-0.052*	0.046	-0.000
	(0.027)	(0.047)	(0.028)
medium rating	-0.038	0.063*	0.019
	(0.030)	(0.033)	(0.024)
cont. R&D	-0.001	0.047**	-0.029**
	(0.021)	(0.024)	(0.014)
East Germany	-0.012	-0.009	-0.023
	(0.025)	(0.026)	(0.016)
industry dummies	*included*	*included*	*included*
time dummies	*included*	*included*	*included*
log likelihood		-709.76	
χ^2 *(all)* [b]		209.14***	
χ^2 *(industries)* [c]		11.80	
χ^2 *(foundation years)* [c]		24.27	
McFadden's R^2		0.128	
McFadden's adjusted R^2		0.044	
Cragg-Uhler's R^2		0.255	
BIC		-3,886.84	
number of observations		855	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the marginal effects of a multinomial logit model with *no change* as base category. Marginal effects are calculated at the sample means. Marginal effects of dummy variables are interpreted as discrete change from 0 to 1. Standard errors are transformed by the delta method. The dependent variable has the following categories: *first replacement*, *first enlargement* and *first reduction*. The Hausman test confirms that the IIA holds.

[a] The *private VC* variable shows whether there has received private VC financing in the period(s) previous to the period of change.

[b] χ^2(all) displays a test of the joint significance of all variables.

[c] χ^2(industries) and χ^2(foundation years) display χ^2-tests of the joint significance of industry and foundation year dummies. Four industry dummies for high-tech 1, high-tech 2, hardware and software are included.

the skills and abilities of the other members more accurately and may conclude that replacing some of them may be a good option.

Our proxy for voluntary exits, the indicator whether at least one manager has already attained the age of 55 at firm foundation has a positive effect on replacement. If at least one person who is 55 years old or older is present in the executive team the probability of replacement with respect to no changes rises by 17 percentage points. The top management holding majority stake at firm foundation are less inclined towards replacement as conjectured. If ownership and control are not separated, i.e. if the executives own the firm, the teams would not opt for replacing members of the top management team.

Continuously conducting R&D activities increases the probability of team enlargement, and decreases the probability of reduction compared to no changes in the team significantly. This confirms that R&D track records will lower the probability of executive dismissal because this firm-specific knowledge, which they will surely incorporate, should not be exposed to the risk of getting lost or even of serving competitors. Furthermore, enlargement becomes more probable, because R&D activities involve a complicated process, and for example, if this process approaches market launch additional knowledge may be indispensable.

But the results presented so far have to be interpreted with caution, since VC financing is possibly endogenous. Endogeneity arises because a strong selection process is underlying the VC involvement, as stated in the literature review in Section 3.2.2. We need to correct for the endogeneity of VC involvement by estimating the probability to receive VC funding and incorporating it in the multinomial logit estimation. Common approaches to account for endogeneity are to use an IV approach, a sort of Heckman selection correction or a two-step approach. But in non-linear models, two-stage models will yield inconsistent estimates.

In the context of multinomial logit, a conventional instrumental variable approach like in Mullahy and Sindelar (1996) does not take into account the non-linearity of the regression function. Instead, we apply a FIML approach as proposed by Terza (2002). In this framework, the underlying latent model of the conventional multinomial model (see McFadden (1973)) is represented as follows:

$$y_r = d\gamma_r + x\beta_r + \nu\theta_r + u \quad \text{for the category} \quad r = 0, 1, 2, 3.$$

where the binary (endogenous) variable d is expressed as the index function,

$$d = I(z\alpha + \nu > 0),$$

i.e. ν captures the combined effects of the unobservable confounders which may be correlated to y and d. z is a vector of instrumental variables including all exogenous variables of the multinomial logit and the identifying variables. The conditional expected values, representing the multinomial logit and simultaneously correcting for the endogeneity of d, are

$$\begin{aligned} E(y_0|d, x, \nu) &= \frac{1}{1 + \sum_{r=1}^{3} exp(d\gamma_r + x\beta_r + \nu\theta_r)} \\ E(y_m|d, x, \nu) &= \frac{exp(d\gamma_m + x\beta_m + \nu\theta_m)}{1 + \sum_{r=1}^{3} exp(d\gamma_r + x\beta_r + \nu\theta_r)}, \end{aligned}$$

for m=1,2,3. The corresponding likelihood function that is maximized using FIML is

$$\mathcal{L}(\alpha, \gamma_m, \beta_m, \theta_m) = \prod_{i=1}^{n} d_i \int_{-z_i\alpha}^{\infty} P_{im}^{y_{im}} \phi(\nu) d\nu + (1 - d_i) \int_{-\infty}^{-z_i\alpha} P_{im}^{y_{im}} \phi(\nu) d\nu,$$

with $i = 1, ..., n$ and where $P_m = E(y_m|d, x, \nu)$. This estimator has no closed-form so that numerical integration procedures apply here. Prof. Terza uses in his program code[24] the Gauss-Legendre quadrature for closed integrals for which 12 is supposed to be the "quasi-infinity" limit of the integrals. So we program this FIML estimator by approximating the one-sidedly bounded integral with the Gauss-Legendre quadrature. This quadrature formula numerically integrates integrals which are bounded two-sidedly. Therefore, we adopt the procedure used by Prof. Terza, and adopt a number reflecting the "quasi-infinity".

[24] We are very grateful to Prof. Terza for providing the Gauss program code which was particularly helpful for determining the numerical integration procedure, e.g. the adoption of quasi infinity, and for transferring the log likelihood in a STATA code.

For identification, instrumental variables need to be included in the equation of VC financing, i.e. we need to find variables which are linked to the probability of VC investment but not to executive turnover. We choose *intermediate* product and the indicator concerning patents before firm foundation (*patent_ before*) as instruments because both should not influence the probability of change but are part of the VC decision. Pre-foundation patenting reflects that the firm uses patents which have been filed before firm foundation, and hence may be seen as a signal for the quality of an innovative firm by VC investors. An intermediate product may reflect that the customers are a quite clearly cut so that the market potential of the product may be less uncertain.

VC financing has now a negative effect on enlargement but no effects on replacement or reduction. We find that the correlation between VC investment and replacement is a mere selection effect, correcting for the selectivity displays no effect of VC-backing. The effect on enlargement is negative which means that VC-backed firms tend less to enlarge their management teams. For private VCCs, we find no significant effect, which also confirms that the positive relation between private VC investment and change in the executive team is only due to selection effects, and that the effect of active involvement on changes can be clearly rejected. Regarding the effects of the control variables, we can confirm most of the ones found in the non-corrected version of the multinomial logit. In the endogeneity-corrected estimation, we find a positive effect of industry experience on the probability of replacement. Furthermore, the effect of continuous R&D remains positive for the probability of enlargement and negative for reduction with respect to no change if we correct for endogeneity. In addition, we find a positive impact of initial firm size on the probability of replacement and enlargement. A positive effect is confirmed on replacement for firms with at least one manager being 55 years old or older and a negative for firms in which the initial management team holds majority stake at firm foundation. The positive enlargement impact of the indicator of academic education can be interpreted similarly to the one of industry experience. It is not necessarily the manager holding an academic degree who is replaced, but he could push for replacement if he concludes that the ability portfolio in the team is unbalanced with respect to the challenges to be addressed.

Table 3.11.: Results for executive turnover using FIML multinomial logit accounting for endogeneity of VC financing

	Multinomial logit for turnover			Switching eq.
Model	**replacement**	**enlargement**	**reduction**	
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
venture capital [a]	-1.161 (0.775)	-1.795** (0.830)	2.569 (2.629)	
cont. R&D	0.118 (0.261)	0.589** (0.275)	-0.788* (0.424)	0.265** (0.121)
m_ graduate	0.567* (0.308)	0.377 (0.316)	0.189 (0.415)	0.299** (0.120)
m_ technical	-0.047 (0.253)	-0.287 (0.270)	0.069 (0.321)	0.041 (0.106)
m_ indexp	0.907*** (0.334)	0.452 (0.332)	-0.120 (0.359)	0.051 (0.119)
m_ above55	1.438*** (0.360)	0.009 (0.507)	-0.109 (0.568)	-0.107 (0.174)
m_ majority	-0.658** (0.311)	-0.263 (0.309)	-0.204 (0.418)	-0.217* (0.118)
log(initial size)	0.567*** (0.164)	0.340* (0.181)	0.170 (0.216)	0.052 (0.070)
log(number team)	0.813*** (0.261)	0.533* (0.283)	1.457*** (0.371)	0.296** (0.121)
good rating	-0.623 (0.398)	0.423 (0.501)	-0.130 (0.577)	0.164 (0.173)
medium rating	-0.334 (0.347)	0.748* (0.454)	0.355 (0.507)	0.111 (0.159)
East Germany	-0.182 (0.321)	-0.200 (0.369)	-0.740 (0.497)	0.240 (0.162)
patent_ before				1.164*** (0.308)
intermediate				-2.989*** (0.249)
constant	-3.213*** (0.651)	-3.514*** (0.702)	-3.239*** (0.819)	-3.888*** (0.363)
industry dummies	*included*	*included*	*included*	*included*
foundation year dummies	*included*	*included*	*included*	*included*
ν	0.917*** (0.298)	0.914*** (0.300)	-1.203 (0.925)	
Log likelihood		-804.46		
LR(endogeneity) [b]		189.48***		
χ^2*(all)* [c]		74.23***		
χ^2*(industries)* [d]		18.91		
χ^2*(foundation year)* [d]		36.38*		
χ^2*(instruments)* [e]		18.90***		
BIC		-3,515.17		
Number of observations		855		

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts coefficients of an endogenous switching multinomial logit model as proposed in Terza (2002) which corrects for the endogeneity of the binary (endogenous) regressor VC financing by estimating simultaneously a multinomial logit model and a probit type VC equation by means of full-information maximum likelihood.

[a] VC variable shows whether there has been VC financing in the period previous to the period of change.

[b] LR(endogeneity) displays a LR-test comparing the endogeneity-corrected multinomial logit to the non-corrected one showing that the endogeneity-corrected model is supposed to be the true one.

[c] χ^2(all) displays a test of the joint significance of all variables.

[d] χ^2(industries) and χ^2(foundation year) display tests of the joint significance of industry and foundation year dummies.

[e] χ^2(instruments) displays a test of the joint significance of instrumental variables in the VC equation.

Table 3.12.: Results for executive turnover using FIML multinomial logit accounting for endogeneity of private VC financing

	Multinomial logit for turnover			Switching eq.
Model	**Replacement**	**enlargement**	**reduction**	
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
private vc [a]	0.172 (0.620)	-1.143 (0.894)	0.603 (1.509)	
cont. R&D	0.046 (0.244)	0.520** (0.259)	-0.594* (0.337)	0.263** (0.123)
m_ graduate	0.497* (0.292)	0.322 (0.302)	0.336 (0.353)	0.295** (0.119)
m_ technical	-0.038 (0.240)	-0.270 (0.257)	0.090 (0.301)	0.047 (0.107)
m_ indexp	0.839*** (0.311)	0.393 (0.314)	-0.075 (0.336)	0.053 (0.121)
m_ above55	1.344*** (0.333)	-0.050 (0.487)	-0.051 (0.542)	-0.088 0.178
m_ majority	-0.608** (0.298)	-0.233 (0.295)	-0.327 (0.380)	-0.203* (0.118)
log(initial size)	0.537*** (0.153)	0.311* (0.171)	0.223 (0.197)	0.052 (0.071)
log(number team)	0.778*** (0.247)	0.514* (0.271)	1.564*** (0.317)	0.285** (0.120)
good rating	-0.616* (0.375)	0.404 (0.487)	-0.054 (0.542)	0.169 (0.174)
medium rating	-0.327 (0.325)	0.776* (0.442)	0.395 (0.481)	0.125 (0.158)
East Germany	-0.182 (0.301)	-0.212 (0.349)	-0.611 (0.438)	0.223 (0.164)
patent_ before				1.302*** (0.305)
intermediate				0.193* (0.108)
constant	-3.017*** (0.601)	-3.388*** (0.670)	-3.306*** (0.766)	-2.997*** (0.253)
industry dummies	*included*	*included*	*included*	*included*
foundation year dummies	*included*	*included*	*included*	*included*
ν	0.512*** (0.175)	0.510*** (0.185)	-0.492 (0.420)	
Log likelihood	-806.74			
LR(endogeneity) [b]	193.96***			
χ^2 *(all)* [c]	83.05***			
χ^2 *(industries)* [d]	18.91			
χ^2 *(foundation year)* [d]	36.68**			
χ^2 *(instruments)* [e]	22.26***			
BIC	-3,510.60			
Number of observations	855			

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts coefficients of an endogenous switching multinomial logit model as proposed in Terza (2002) which corrects for the endogeneity of the binary (endogenous) regressor private VC financing by estimating simultaneously a multinomial logit model and a probit type private VC equation by means of full-information maximum likelihood.

[a] *Private VC* shows whether there has been private VC financing in the period previous to the period of change.

[b] LR(endogeneity) displays a LR-test comparing the endogeneity-corrected multinomial logit to the non-corrected one showing that the endogeneity-corrected model is supposed to be the true one.

[c] χ^2(all) displays a test of the joint significance of all variables.

[d] χ^2(industries) and χ^2(foundation year) display tests of the joint significance of industry and foundation year dummies.

[e] χ^2(instruments) displays a test of the joint significance of instrumental variables in the private VC equation.

3.4.3.2. Determinants of the time to first change

In order to investigate which impact factors influence the point in time when changes in the initial founding team take place, we use survival analysis. With the aid of these models, we can estimate the risk of executive turnover within the next period given that the team has not been subject to changes before. A widely used model is the Cox proportional hazard model (Cox (1972)).

As mentioned before, we cannot identify the exact date when a change occurred but only the year of occurrence. Consequently, if we observe a change in the top management we refer to a spell of one year in which the event took place. In contrast to continuous survival models, like the Cox proportional hazard, events of change may be clustered in one time period for which the ordering of occurrence is unknown, so-called tied observations. In this context, one should rely on discrete-time transition models (see Cameron, Trivedi (2005), pp. 602) which are represented as

$$Pr(t_{a-1} \leq T < t_a | T \geq t_{a-1} | x) = F(\lambda_a + x(t_{a-1})\beta),\ a = 1, \ldots, A,$$

i.e. the probability of change occurrence (T) within the time span between t_{a-1} and t_a given that T will occur at or after t_{a-1}, conditional on regressors x, is represented by a cumulative distribution function (cdf) including time-constant coefficients of regressors x and a time-variant intercept λ_a. The dependent variable is represented as an indicator of the occurrence of a change within the time span at observation. According to the choice of F, the parameters λ_a and β can be estimated by first expanding the data set, so that one observation reflects a company-year and then estimating a stacked discrete choice model. F is represented by the extreme value cdf. Hence, we estimate a complementary log-log model (cloglog) of the following form

$$F(\lambda_a + x(t_{a-1})\beta) = 1 - exp(-exp(\lambda_a + x(t_{a-1})\beta)).$$

The likelihood corresponds to

$$\mathcal{L}(\beta, \lambda_1, \ldots, \lambda_A) = \prod_{i=1}^{N} \left[\prod_{s=1}^{a_i - 1} \Big(exp(-exp(ln(\lambda_s + x_i(t_{s-1})\beta))) \Big) \right] \times F\Big(exp(-exp(ln(\lambda_{a_i} + x_i(t_{a-1})\beta))) \Big).$$

Cloglog models are the discrete counterpart to a continuous-time proportional hazard model. An advantage of cloglog is that it appropriately represents rare events which may cause problems here since our dependent variable is binary and contains many zeros[25]. This is the case because we have amplified the data set, so that for each firm we have multiple observations and maximal one unit value for the indication of change. Moreover, the data is strongly right-censored meaning that many firms may experience a change but after the observation period. λ_a can be interpreted as the baseline hazard which has to be parameterized. We have decided to use $\lambda_a = log(t_a)$[26].

Furthermore, in duration analysis, we must account for unobserved heterogeneity since ignoring it may cause confounding its impact with that of the baseline hazard, i.e. ignoring it will lead to overestimating the degree of negative duration dependence. To account for unobserved heterogeneity, a heterogeneity term is added. We assume that in our discrete duration setting heterogeneity is normally distributed. The inclusion of the heterogeneity term ν_i can be represented as

$$\epsilon_i = ln \left(\int \lambda_0(\tau) d\tau \right) - x_i\beta - \nu_i, \tag{3.1}$$

where $\epsilon_i = \Lambda_0(t) - x_i\beta$ including the hetergeneity term ν_i. Inserting Equation 3.1 into the following log likelihood function results in an estimator of discrete proportional hazard with Gamma heterogeneity:

$$ln\mathcal{L}(\beta, \Lambda_0(1), \ldots, \Lambda_0(T)) = \sum_{i=1}^{N} \sum_{t=1}^{T} y_{it} ln \left[\int_{\Lambda_0(t-1)-x_i\beta}^{\Lambda_0(t)-x_i\beta} f(\epsilon) d\epsilon \right],$$

[25] King and Zeng (2001) claim that standard logistic regressions sharply underestimate the probability of rare events.

[26] The results are presented in Table B.4 and B.5 (pp. 218 and 219) in the Appendix.

where $\Lambda_0(t)$ is the integrated baseline hazard.

Table 3.13 and 3.14 display the results in hazard ratios for VC and private VC funding[27]. The Hazard ratios are evaluated at unit value, i.e. a significant ratio above (below) one is interpreted relative to "no changes in the management team" as positive (negative) effect. We find for VC a highly significant positive effect on replacement. This is interpreted as the risk of a firm to experience a change in the next period being significantly higher for VC-backed firms than for non-VC-backed. In other words, changes in the executive teams will occur earlier if firms are VC-backed. As concerns private VC financing, we also find a positive significant effect.

As regards management and firm characteristics, we see that those which are found to influence the probability of a specific kind of change (see previous section) also influence the timing until change occurs. Changes in the executive team will occur earlier if the initial team is larger. The risk of discord in the management team may increase with its number. If the initial management team holds majority stake the firm is more reluctant towards replacing at least parts of the team.

Furthermore, larger initial size leads to earlier replacement which hints at the complexity of the organization in larger firms and the challenges of it. Industry experience of the management team increases the probability of replacement (see previous section), and replacement occurs earlier if this characteristic is present in the management team. As before, we can argue that the indicator of industry experience only displays that at least one member has got this characteristics. A positive contribution may thus be interpreted such that experienced managers will be able to realize earlier if things go wrong, or if specific skills are needed which are not present in the current team, and may push for exchanging or enlarging earlier. Management teams with at least one member of the age of 55 or above experience replacement earlier.

Furthermore, the probability of top management enlargement within the subsequent period increases if the firm continuously performs R&D activities but lowers the probability of reduction in the next period. The effect on enlargement displays that the complexity of the R&D process may call for further abilities which are not present in the initial team and the effect of reduction displays the long-term character of R&D

[27]The LR test of the significance of ρ suggest that unobserved heterogeneity is not an issue in this context. The results of cloglog models without heterogeneity are displayed in the Appendix in Table B.4 and B.5. The results remain basically the same.

Table 3.13.: Cloglog models for VC financing with unobserved heterogeneity for time until first change

	Replacement	Enlargement	Reduction
	Haz.Rat. (Std.Err.)	**Haz.Rat. (Std.Err.)**	**Haz.Rat. (Std.Err.)**
venture capital [a]	2.625***	1.503	0.735
	(0.628)	(0.624)	(0.429)
log(number team)	2.229***	1.653**	3.971***
	(0.381)	(0.418)	(1.519)
log(initial size)	1.143***	1.057	1.055
	(0.056)	(0.073)	(0.077)
m_graduate	1.294	1.174	1.647
	(0.304)	(0.328)	(0.556)
m_technical	0.931	0.775	1.149
	(0.172)	(0.182)	(0.321)
m_indexp	1.868**	1.602	1.141
	(0.458)	(0.479)	(0.358)
m_above55	2.594***	0.840	1.128
	(0.599)	(0.346)	(0.512)
m_majority	0.647*	0.806	0.551
	(0.154)	(0.219)	(0.201)
good rating	0.691	1.586	0.955
	(0.189)	(0.704)	(0.447)
medium rating	0.752	2.236*	1.119
	(0.183)	(0.928)	(0.473)
cont. R&D	1.000	1.914***	0.523**
	(0.184)	(0.473)	(0.171)
East Germany	0.965	0.810	0.741
	(0.211)	(0.256)	(0.277)
log(t)	0.637***	0.668	1.145
	(0.092)	(0.168)	(0.364)
constant	0.017***	0.006***	0.005***
	(0.008)	(0.006)	(0.006)
industry dummies	*included*	*included*	*included*
σ_u [b]	0.236	1.005	0.999
	(0.819)	(0.827)	(0.939)
ρ	0.236	0.380	0.378
	(0.220)	(0.388)	(0.437)
log likelihood	-540.50	-440.13	-339.01
χ^2 *(all)* [c]	131.65***	49.46***	34.49***
χ^2 *(industries)* [c]	4.08	6.98	3.44
LR-test($\rho = 0$) [d]	0.02	0.48	0.25
BIC	-33,587.40	-33,421.78	-33,373.10
number of observations	4,177	4,138	4,111

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the hazard ratios of cloglog duration models with unobserved normally distributed heterogeneity. The dependent variables are *time until first replacement*, *time until first enlargement* and *time until first reduction*.

[a] VC variable shows whether there has been VC financing in the period previous to the period of change.

[b] σ_u is the panel-level standard deviation.

[c] χ^2(all) and χ^2(industries) display tests on the joint significance of all variables and of the industry dummies.

[d] The LR-test shows whether ρ is significant, i.e. whether heterogeneity needs to be accounted for.

Table 3.14.: Cloglog models for private VC financing with unobserved heterogeneity for time until first change

	Replacement	Enlargement	Reduction
	Haz.Rat. **(Std.Err.)**	**Haz.Rat.** **(Std.Err.)**	**Haz.Rat.** **(Std.Err.)**
private vc [a]	3.317***	1.579	0.483
	(0.847)	(0.797)	(0.389)
log(number team)	2.188***	1.723**	4.029***
	(0.370)	(0.460)	(1.538)
log(initial size)	1.163***	1.068	1.052
	(0.056)	(0.076)	(0.077)
m_graduate	1.274	1.192	1.658
	(0.295)	(0.349)	(0.562)
m_technical	0.938	0.766	1.154
	(0.170)	(0.191)	(0.323)
m_indexp	1.877***	1.664	1.147
	(0.449)	(0.528)	(0.361)
m_above55	2.630***	0.825	1.122
	(0.555)	(0.359)	(0.510)
m_majority	0.653*	0.805	0.546*
	(0.153)	(0.230)	(0.199)
good rating	0.741	1.627	0.945
	(0.198)	(0.754)	(0.443)
medium rating	0.765	2.325*	1.128
	(0.183)	(1.009)	(0.478)
cont. R&D	1.022	1.996***	0.522**
	(0.186)	(0.517)	(0.171)
East Germany	1.014	0.821	0.734
	(0.219)	(0.275)	(0.275)
log(t)	0.635***	0.714	1.149
	(0.084)	(0.191)	(0.365)
constant	0.018***	0.004***	0.004***
	(0.007)	(0.005)	(0.006)
industry dummies	*included*	*included*	*included*
σ_u [b]	0.007	1.005	0.999
	(0.052)	(0.827)	(0.939)
ρ	0.000	0.380	0.378
	(0.000)	(0.388)	(0.437)
log likelihood	-538.87	-440.15	-335.34
χ^2*(all)* [c]	148.34***	45.15***	34.60***
χ^2*(industries)* [c]	0.44	6.51	4.02
LR-test($\rho = 0$) [d]	0.00	1.27	0.28
BIC	-33,907.05	-33,732.37	-33,692.40
number of observations	4,177	4,138	4,111

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the hazard ratios of cloglog duration models with unobserved normally distributed heterogeneity. The dependent variables are *time until first replacement*, *time until first enlargement* and *time until first reduction*.

[a] Private VC variable shows whether there has been VC financing in the period previous to the period of change.

[b] σ_u is the panel-level standard deviation.

[c] χ^2(all) and χ^2(industries) display tests on the joint significance of all variables and of the industry dummies.

[d] The LR-test shows whether ρ is significant, i.e. whether heterogeneity needs to be accounted for.

investment and the before mentioned fact that R&D track records lead to a lower probability of getting exchanged (see Jain, Tabak (2008) and Section 3.4.2). All effects are as expected and are in line with the results of the previous section, i.e. besides the increase in probability the respective characteristic also has the same effect on timing of changes. Variables increasing the probability of change also increase the risk of earlier occurrence.

As we observe three different kinds of change, an alternative specification of the duration is the so-called competing risks model, which can be represented in the case of Cox proportional hazard as

$$h_j(t|x) = \lambda_j(t)exp(x\beta_j),$$

where j represents different types of risk, in our case replacement, reduction and enlargement. In these models, correlations between unobservable factors affecting each risk-specific hazard are usually assumed to be zero, hence the log-likelihood can be separated into a sum of likelihoods for each risk-type. When it comes to the application of competing-risk hazards to discrete time models, the separability is not given anymore and modeling is more complex. Only if one assumes that transitions to the different risk-types can only occur at the boundaries of the intervals, estimation gets relatively straightforward. Since this is a very strong assumption, which does very likely not reflect the data best, we only present the results in the Appendix in Tables B.6 and B.7 (pp. 220 and 221). The results are basically the same as for the cloglog models. Actually, we should estimate a risk-competing discrete duration model with unobserved heterogeneity. But since already the discrete modeling of risk-competing duration is challenging the inclusion of a heterogeneity term may even be more complicated.

As in Section 3.4.3.1, we should also account for endogeneity of VC financing in the context of duration analysis. Abbring and van den Berg (2003) present a nonparametric approach for this issue, and van den Berg et al. (2004) show an empirical application for sanction rules regarding unemployment. They derive the model for continuous spell data. The transition rate at time t relates to a Mixed Proportional Hazard.

$$h_j(t|x, \nu_j, t_s) = \lambda_j(t_j|x, \nu_j, t_s)exp\left[x\beta_j + \delta I(t_s < t) + \nu_j\right],$$

where δ is the treatment and $I(t_s < t)$ is an indicator function showing unit value if $t_s < t$, i.e. if the treatment occurs previously. Furthermore, the treatment rate at t conditional on observed and unobserved characteristics x and ν_s is modeled as

$$h_s(t|x, \nu_s) = \lambda_s(t) exp\left[x\beta_s + \nu_s\right],$$

Implementations is highly demanding. Furthermore, to our knowledge there is no model for treatment effects in discrete duration models. Hence, we renounce to program an endogeneity-corrected duration model.

This means that the findings in this section need to be interpreted rather as correlations than as causal effects. The estimation of several duration models (cloglog without and with unobserved heterogeneity, competing-risk models) show that the effect of VC financing is robust. But reminding the results of the previous section which show that the impact of VC financing on executive replacement is a mere selection issue, we suspect that if we controlled for the selectivity the effect on timing would vanish as well. This issue would be part of future research.

3.4.3.3. The impact of changes in top management on firm performance

Tables 3.15 and 3.16 depict estimation results for firm growth and labor productivity. The aim is to test whether VC financing and (the number of) changes have an impact on firm performance. Looking at the estimation of differences between the initial and the latest labor productivity the stylized facts can be confirmed. A negative effect of firm age is found. This effect reflects that established firms have a lower difference in labor productivity than younger firms. Firm age is correlated with firm size (in this respect the firm size at the time before the last observation of labor productivity). Moreover, we find a negative effect for East German firms with respect to West German firms which is also as conjectured, and a negative effect of initial labor productivity hinting at convergence in this measure. These effects already explain a large part of the variance of the differences in labor productivity. Furthermore, we control for management characteristics in order to test whether those have an impact on performance. We confirm a positive effect of the initial team size, i.e. firms with larger top management at foundation would thus exhibit a better performance in terms of labor productivity. Larger teams may be better able to cover the abilities necessary for managing a company. Finally, we confirm a positive significant effect for private VCCs meaning that the presence of an active investor positively influences the performance of the firms. Changes in the management team have no significant effects.

As regards the growth equations we also find some expected effects: younger firms exhibit a higher short-term growth figure than older ones as the firm age variable has a significant negative effect. Furthermore, we find no significant effect for East German firms hinting at the fact that regarding firm growth East German firms do not lag behind anymore. Surprisingly, the initial size has no effect on growth. But as we take firm age into account which in other studies is often supposed to approximate the current firm size, the size effect may already be incorporated in the firm age variable. Hence, firm age may reflect the firm size at the time before observing growth. But, as already discussed in Section 3.4.2, we are not able to observe employment this frequently to adequately account for size effects without a substantial loss of observations. For the growth equations, we can further confirm a negative impact of (the number of) executive team reduction(s). Team reductions may be observed if top management teams are inefficient or if past firm growth (or more accurately firm shrinking) does not justify a large team, hence the firm may have reached a size which may call for a smaller management team[28]. If a firm experienced a bad performance and shrink and if the reductions in the top management are sufficient, the resulting changes in organization would need time to manifest and to yield fruit. Hence, a larger lag between the occurrence of change and firm performance should be taken into account. Unfortunately, we do not have a longer times series.

To account for the selectivity of VC investment decision as in Section 3.4.3.1, we use a two-step selection model as described in Greene (2003). The basic idea is that because VC financing is endogenous the results of firm performance can only be interpreted

[28] Clearly, the R^2 is very small in the growth estimations which hints at the fact that the variations in firm growth are to a large extent not captured by the included regressors. This may be an indication for omitted variables. We are aware of the possibility that there may be unobserved effects. If the omitted variable would be correlated with the included regressors this would pose a problem since the estimates of the included regressors get inconsistent. Therefore, we test for omitted variables using the Ramsey RESET test and find no evidence for omitted variables. The RESET test is not a strong test for detecting omitted variables since it basically tests for misspecifications of the functional form, and hence also treats the omitted variables problem as a sort of functional misspecification. Its performance is particularly poor if the omitted variable can be linearly presented in terms of the regressor(s) (see Wooldridge (2002) for discussion). But it may provide a hint that the omitted variable problem may not be that pronounced and the lacking explanation in the variation of the dependent variable can either be explained by uncorrelated omitted variables or be random shocks.

Table 3.15.: Results for firm performance with VC and changes to top management team

Model	Growth		Δ Labor productivity	
	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)
venture capital[a]	0.035 (0.967)	0.041 (0.067)	0.135 (0.164)	0.126 (0.160)
replacement[a]	-0.004 (0.042)		0.083 (0.164)	
enlargement[a]	0.008 (0.038)		-0.138 (0.133)	
reduction[a]	-0.084** (0.042)		0.008 (0.198)	
number replacement[a]		-0.018 (0.030)		0.041 (0.100)
number enlargement[a]		0.019 (0.035)		-0.187 (0.137)
number reduction[a]		-0.097*** (0.036)		0.152 (0.189)
log(number team)	-0.024 (0.028)	-0.021 (0.028)	0.149* (0.082)	0.141* (0.081)
m_ graduate	-0.024 (0.036)	-0.023 (0.036)	0.022 (0.094)	0.027 (0.094)
m_ technical	0.023 (0.030)	0.022 (0.030)	-0.120 (0.088)	-0.125 (0.088)
m_ indexp	-0.001 (0.041)	-0.001 (0.040)	-0.078 (0.100)	-0.072 (0.100)
m_ majority	-0.134 (0.158)	-0.036 (0.036)	-0.000 (0.084)	0.003 (0.085)
good rating	-0.089 (0.056)	-0.090 (0.056)	-0.163 (0.134)	-0.165 (0.133)
medium rating	-0.086* (0.051)	-0.084 (0.051)	-0.039 (0.129)	-0.045 (0.127)
cont. R&D	0.048 (0.034)	0.048 (0.033)	0.086 (0.092)	0.094 (0.093)
log(firm age)	-0.014** (0.007)	-0.013* (0.007)	-0.066*** (0.022)	-0.067*** (0.022)
log(initial size)	0.001 (0.008)	0.002 (0.008)		
$log(labor\ productivity_0)$			-0.687*** (0.061)	-0.691*** (0.061)
East Germany	-0.013 (0.039)	-0.013 (0.039)	-0.266** (0.123)	-0.262** (0.123)
constant	0.346*** (0.078)	0.345*** (0.077)	-0.745*** (0.211)	-0.746*** (0.210)
industry dummies	included	included	included	included
log likelihood	-209.34	-207.70	-663.90	-662.98
F(all)[b]	1.49*	1.64**	9.63***	9.66***
F(industries)[c]	2.18*	2.18*	2.56**	2.52**
Adjusted R^2	0.014	0.019	0.220	0.222
BIC	-3,203.31	-3,206.58	-1,691.12	-1,692.95
number of observations	588	588	505	505

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of OLS estimations on changes in firm growth and labor productivity. Robust standard Errors are in parentheses.
[a] Variables indicating that the event occurred previous to the observation time of the dependent variable.
[b] F(all) displays a F-test of the joint significance of all variables.
[c] F(industries) displays a F-test of the joint significance of industry dummies.

Table 3.16.: Results for firm performance with private VC and changes to top management team

Model	Growth		Δ Labor productivity	
	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)
private vc [a]	0.116 (0.081)	0.124 (0.080)	0.531* (0.281)	0.515* (0.262)
replacement [a]	-0.009 (0.041)		0.048 (0.164)	
enlargement [a]	0.005 (0.039)		-0.136 (0.130)	
reduction [a]	-0.084** (0.042)		0.004 (0.192)	
number replacement [a]		-0.021 (0.030)		0.019 (0.099)
number enlargement [a]		0.016 (0.036)		-0.181 (0.136)
number reduction [a]		-0.098*** (0.036)		0.134 (0.175)
log(number team)	-0.025 (0.028)	-0.022 (0.028)	0.141* (0.082)	0.134 (0.081)
m_graduate	-0.027 (0.036)	-0.026 (0.036)	0.021 (0.094)	0.025 (0.094)
m_technical	0.022 (0.030)	0.021 (0.030)	-0.114 (0.087)	-0.119 (0.087)
m_indexp	0.001 (0.040)	0.001 (0.040)	-0.083 (0.099)	-0.077 (0.099)
m_majority	-0.030 (0.036)	-0.033 (0.036)	0.008 (0.084)	0.009 (0.084)
good rating	-0.089 (0.056)	-0.090 (0.056)	-0.157 (0.134)	-0.158 (0.133)
medium rating	-0.087* (0.051)	-0.085* (0.051)	-0.031 (0.129)	-0.037 (0.127)
cont. R&D	0.048 (0.033)	0.048 (0.033)	0.085 (0.091)	0.093 (0.091)
log(firm age)	-0.014** (0.007)	-0.013* (0.007)	-0.066*** (0.022)	-0.067*** (0.022)
log(initial size)	0.001 (0.008)	0.002 (0.008)		
$log(labor\ productivity_0)$			-0.686*** (0.060)	-0.690*** (0.060)
East Germany	-0.012 (0.039)	-0.012 (0.039)	-0.257** (0.124)	-0.255** (0.123)
constant	0.345*** (0.078)	0.344*** (0.077)	-0.755*** (0.210)	-0.755*** (0.209)
industry dummies	included	included	included	included
log likelihood	-207.93	-206.13	-460.60	-660.67
F(all) [b]	1.60*	1.77**	10.27***	10.22***
F(industries) [c]	2.18*	2.19*	2.61**	2.56**
Adjusted R^2	0.018	0.024	0.227	0.230
BIC	-3,206.13	-3,209.72	-1,695.98	-1,697.57
number of observations	588	588	505	505

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of OLS estimations on changes in firm growth and labor productivity.
[a] Variables indicating that occurred previous to the observation time of the dependent variable.
[b] F(all) displays an F-test of the joint significance of all variables.
[c] F(industries) displays an F-test of the joint significance of industry dummies.

conditional on VC- or non-VC-financing. According to Heckman and Smith (1996), this is associated this with a problem of lacking data. The consequence is that the error term needs also to be expressed as conditional on the VC financing state (F) and the other regressors (X) and $E(U|F, X) \neq 0$. Thus, the OLS estimation would be biased. To deal with this problem, the error term U is split into two parts conditional on the altering VC financing state and a component U^* which is independent of F:

$$E(U|F, X) = E(U|X, F, Z) + U^*,$$

and Z contains additional regressors of the selection equation. An indicator function is estimated in which the state of the treatment is related to Z, which is called selection equation. The error terms of the selection and the structural equation for performance are independent of the regressors X and Z. Assuming that the error terms are jointly normally distributed, the so-called mill's ratio can account as selection correction term (Heckman (1979)).

In a first step, we estimate a probit equation

$$F = Z\gamma + \epsilon.$$

For each observation in the sample, we compute the mill's ratio defined as

$$\hat{\lambda} = \frac{\phi(\hat{\gamma}Z)}{\Phi(\hat{\gamma}Z)}.$$

where ϕ is the standard normal and Φ the cumulative normal distribution and $\hat{\gamma}$ are the coefficients of a first stage probit.

In a second step, we estimate a least squares regression:

$$Y = \beta X + \alpha F + \beta_\lambda \hat{\lambda} + U^*,$$

where $\beta_\lambda = \rho\sigma_\epsilon$[29].

[29] σ_ϵ are the standard errors of the first stage and ρ is the correlation between ϵ and U.

If we control for the selectivity of VC investors (see Tables 3.17 and 3.18), we find that the effects of private VCCs are positive on both labor productivity and firm growth. Hence, return-oriented VC investors contribute positively to the performance of their portfolio firms which may be due to the more intense active involvement. All other effects found in the previous estimations are found as well[30].

Table 3.17.: Selection-corrected results for firm performance with VC financing and changes to top management team

Model	Growth		Δ Labor productivity	
	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)
venture capital [a]	0.036 (0.053)	0.042 (0.053)	0.134 (0.165)	0.126 (0.161)
replacement [a]	-0.005 (0.042)		0.083 (0.164)	
enlargement [a]	0.008 (0.041)		-0.138 (0.133)	
reduction [a]	-0.084* (0.045)		0.007 (0.106)	
number replacement [a]		-0.018 (0.030)		0.041 (0.099)
number enlargement [a]		0.020 (0.036)		-0.187 (0.138)
number reduction [a]		-0.097** (0.038)		0.152 (0.187)
log(number team)	-0.020 (0.037)	-0.016 (0.037)	0.146 (0.125)	0.145 (0.122)
m_graduate	-0.014 (0.067)	-0.011 (0.067)	0.019 (0.126)	0.031 (0.124)
m_technical	0.025 (0.031)	0.023 (0.031)	-0.121 (0.093)	-0.125 (0.093)

(To be continued on next page)

[30] Clearly, the different categories of changes included as explanatory variables may also be endogenous. Particularly for the estimation of the differences in labor productivity, this problem may be relevant because the difference is measured for the whole period. But if we contemporaneously control for selectivity this endogeneity issue is even more difficult to address. Especially, finding valid instruments would be very challenging with the data set at hand. Therefore, we tested for omitted variables in the corrected and non-corrected version and find no evidence that there is a problem of omitted variables (see footnote 28 for a discussion of problems with the RESET test).

Model	**Growth**		**Δ Labor productivity**	
	Coef. (Std.Err.)	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**
m_ indexp	-0.003	-0.003	-0.080	-0.069
	(0.038)	(0.038)	(0.127)	(0.124)
m_ majority	-0.036	-0.039	0.000	0.002
	(0.037)	(0.037)	(0.084)	(0.085)
good rating	-0.085	-0.085	-0.169	-0.158
	(0.057)	(0.057)	(0.201)	(0.199)
medium rating	-0.082	-0.080	-0.044	-0.039
	(0.051)	(0.051)	(0.169)	(0.168)
cont. R&D	0.053	0.054	0.080	0.102
	(0.042)	(0.041)	(0.169)	(0.168)
log(firm age)	-0.014*	-0.014*	-0.066***	-0.067***
	(0.007)	(0.007)	(0.022)	(0.022)
log(initial size)	0.002	0.003		
	(0.009)	(0.009)		
$log(labor\ productivity_0)$			-0.687***	-0.691***
			(0.061)	(0.061)
East Germany	-0.011	-0.010	-0.271*	-0.257*
	(0.041)	(0.040)	(0.156)	(0.155)
constant	0.305	0.296	-0.705	-0.794
	(0.240)	(0.240)	(1.076)	(1.794)
industry dummies	included	included	included	included
λ	0.015	0.018	0.070	0.018
	(0.084)	(0.084)	(0.177)	(0.388)
log likelihood	-209.32	-207.68	-663.90	-662.98
F(all) [b]	1.36	1.53*	9.14***	9.22***
F(industries) [c]	1.79	1.80	2.00*	2.02*
Adjusted R^2	0.012	0.018	0.218	0.221
BIC	-3,196.96	-3,200.25	-1,684.89	-1,686.72
number of observations	588	588	505	505

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of two-step selection models (second stage) on changes in firm growth and labor productivity.

[a] Variables indicating that the event occurred previous to the observation time of the dependent variable.

[b] F(all) displays a F-test of the joint significance of all variables.

[c] F(industries) displays a F-test of the joint significance of industry dummies.

Table 3.18.: Selection-corrected results for firm performance with private VC financing and changes to top management team

Model	Growth		Δ Labor productivity	
	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)
private vc [a]	0.117* (0.066)	0.126* (0.065)	0.541* (0.282)	0.525** (0.263)
replacement [a]	-0.009 (0.042)		0.052 (0.163)	
enlargement [a]	0.005 (0.041)		-0.137 (0.130)	
reduction [a]	-0.084* (0.045)		0.004 (0.192)	
number replacement [a]		-0.021 (0.029)		0.021 (0.099)
number enlargement [a]		0.016 (0.036)		-0.181 (0.136)
number reduction [a]		-0.098*** (0.038)		0.135 (0.176)
log(number team)	-0.022 (0.033)	-0.019 (0.032)	0.213 (0.145)	0.206 (0.144)
m_ graduate	-0.016 (0.067)	-0.013 (0.067)	0.075 (0.103)	0.078 (0.103)
m_ technical	0.023 (0.031)	0.022 (0.031)	-0.147 (0.096)	-0.151 (0.096)
m_ indexp	-0.000 (0.038)	-0.001 (0.038)	-0.014 (0.143)	-0.010 (0.143)
m_ majority	-0.036 (0.045)	-0.040 (0.045)	-0.058 (0.123)	-0.056 (0.123)
good rating	-0.088* (0.052)	-0.089* (0.052)	-0.161 (0.133)	-0.163 (0.132)
medium rating	-0.085* (0.048)	-0.083* (0.048)	-0.043 (0.127)	-0.048 (0.125)
cont. R&D	0.050 (0.033)	0.051 (0.033)	0.125 (0.102)	0.132 (0.103)
log(firm age)	-0.014* (0.007)	-0.013* (0.007)	-0.060*** (0.023)	-0.061*** (0.022)

(To be continued on next page)

Model	**Growth**		**Δ Labor productivity**	
	Coef. (Std.Err.)	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**
log(initial size)	0.002	0.003		
	(0.009)	(0.009)		
log(labor productivity$_0$)			-0.688***	-0.692***
			(0.060)	(0.060)
East Germany	-0.013	-0.012	-0.255**	-0.253**
	(0.039)	(0.039)	(0.124)	(0.123)
constant	0.305	0.299	-1.297	-1.289
	(0.211)	(0.211)	(0.804)	(0.803)
industry dummies	included	included	included	included
λ	0.014	0.016	0.189	0.186
	(0.068)	(0.068)	(0.260)	(0.260)
log likelihood	-207.91	-206.10	-661.14	-660.36
F(all) [b]	1.50*	1.69**	9.73***	9.68***
F(industries) [c]	2.03*	3.03*	2.81**	2.79**
Adjusted R^2	0.017	0.023	0.226	0.229
BIC	-3,199.79	-3,203.40	-1,690.40	-1,691.96
number of observations	588	588	505	505

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of two-step selection models (second stage) on changes in firm growth and labor productivity.
[a] Variables indicating that the event occurred previous to the observation time of the dependent variable.
[b] F(all) displays a F-test of the joint significance of all variables.
[c] F(industries) displays a F-test of the joint significance of industry dummies.

As a robustness check, we further perform the regressions with interactions between the VC financing indicator and the different types of changes to further shed light into the various mechanisms that may be at work in this respect. Since we presume that VC investors are highly selective regarding their investment opportunities, and consequently the VC dummy would be endogenous, the interaction terms of the endogenous dummy and the presumably exogenous variables are themselves endogenous. In this case, finding valuable instruments is very hard, particularly for the endogenous interaction terms. Since the mill's ratios in the selectivity-corrected models, are not significant, we could act on the assumption that the selectivity issue of VC financing is not so pronounced as concerns performance issues regarding firm growth and labor productivity. Hence, no selectivity-corrected model is run.

In Tables 3.19 and 3.20 the results for the OLS regressions with interaction terms are displayed. According to the findings, the VC dummy is significantly positive, i.e. VC-backed firms experiencing no changes have a positive effect as regards firm growth; this effect is even stronger for private VCCs. The differences of both effects are significant at the 1 % level, i.e. the active involvement in terms of management support beyond changing the executive team contributes to a higher short-term growth level. Furthermore, VC-induced enlargements as well as the number of VC-induced replacements have a negative effect on growth. Since a higher number of changes is supposed to take place if previous growth did not show the expected pattern and a negative effect is found, this may be the result of two effects: First, changes in the team have been such that disruptive effects occurred in the firms' processes and routines which may be harmful for the firm performance. This effect could be particularly pronounced if the top management experiences replacement. Second, the newly composed executive team was not yet able to leave its prints and to enhance firm performance. This effect could be eliminated if we had a longer time series and observed the performance measures with a longer distance to the observation period. Generally, effects on performance can be expected to become manifest with a lag of several years after changing the top management. For labor productivity, we find a positive effect of VC-induced reductions. Hence, firms experiencing VC-induced reductions improve their performance after changes occurred. As regards the robustness check of private VCCs, we find for growth basically the same effects. Concerning labor productivity we confirm positive effects of VC-induced enlargements and reductions. Thus, the positive effect of private VC involvement found in the previous regressions (see Tables 3.17 and 3.16) can be attributed to the active involvement particularly regarding the composition of the top management. Hence, return-oriented VC investors seem to have an impact on performance in terms of labor productivity if they push for changes in the top management.

Table 3.19.: Results for firm performance with VC and changes to top management team with interactions

Model	**Growth**		**Δ Labor productivity**	
	Coef. (Std.Err.)	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**
venture capital	0.165*	0.159*	-0.186	-0.157
	(0.088)	(0.082)	(0.187)	(0.183)
replacement	0.012		0.035	
	(0.041)		(0.186)	
enlargement	0.046		-0.198	
	(0.039)		(0.132)	
reduction	-0.074*		-0.142	
	(0.043)		(0.191)	
*vc*replacement*	-0.110		0.327	
	(0.130)		(0.311)	
*vc*enlargement*	-0.294**		0.468	
	(0.137)		(0.430)	
*vc*reduction*	-0.061		1.070	
	(0.154)		(0.709)	
number replacement		0.004		-0.004
		(0.032)		(0.123)
number enlargement		0.063*		-0.200
		(0.035)		(0.145)
number reduction		-0.089**		-0.059
		(0.038)		(0.155)
*vc*number replacement*		-0.085		0.170
		(0.065)		(0.167)
*vc*number enlargement*		-0.268**		0.257
		(0.108)		(0.412)
*vc*number reduction*		0.012		1.014*
		(0.106)		(0.541)
log(number team)	-0.026	-0.028	0.148*	0.148*
	(0.028)	(0.028)	(0.083)	(0.083)
m_graduate	-0.027	-0.023	0.027	0.034
	(0.036)	(0.036)	(0.095)	(0.095)
m_technical	-0.025	0.024	-0.099	-0.096
	(0.030)	(0.030)	(0.087)	(0.086)
m_indexp	-0.018	-0.021	-0.059	-0.050
	(0.041)	(0.041)	(0.102)	(0.102)

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Model	Growth		Δ Labor productivity	
	Coef. (Std.Err.)	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**
m_ majority	-0.035	-0.037	-0.005	-0.002
	(0.036)	(0.036)	(0.085)	(0.086)
good rating	-0.082	-0.083	-0.184	-0.184
	(0.056)	(0.056)	(0.134)	(0.132)
medium rating	0.081	-0.081	-0.051	-0.059
	(0.052)	(0.051)	(0.129)	(0.127)
cont. R&D	0.053	0.049	0.060	0.062
	(0.033)	(0.033)	(0.091)	(0.090)
log(firm age)	-0.014**	-0.014**	-0.069***	-0.068***
	(0.007)	(0.007)	(0.022)	(0.022)
log(initial size)	0.003	0.003		
	(0.008)	(0.008)		
$log(labor\ productivity_0)$			-0.692***	-0.695***
			(0.061)	(0.061)
East Germany	-0.008	-0.006	-0.255**	-0.260**
	(0.039)	(0.039)	(0.120)	(0.117)
constant	0.345***	0.348***	-0.722***	-0.738***
	(0.077)	(0.077)	(0.211)	(0.211)
industry dummies	included	included	included	included
log likelihood	-204.73	-202.25	-658.78	-656.08
F(all)	1.62**	0.85	8.80***	8.83***
F(industries)	2.08*	2.03*	2.44**	2.41**
Adjusted R^2	0.024	0.032	0.231	0.239
BIC	-3,193.39	-3,198.36	-1,682.68	-1,688.08
number of observations	588	588	505	505

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of OLS estimations on changes in firm growth and labor productivity. Robust standard Errors are in parentheses.

[a] Variables indicating that the event occurred previous to the observation time of the dependent variable.

[b] F(all) displays a F-test of the joint significance of all variables.

[c] F(industries) displays a F-test of the joint significance of industry dummies.

Table 3.20.: Results for firm performance with private VC and changes to top management team with interactions

Model	Growth		Δ Labor productivity	
	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)
private vc	0.303***	0.292***	0.202	0.143
	(0.117)	(0.105)	(0.260)	(0.239)
replacement	0.015		0.085	
	(0.042)		(0.176)	
enlargement	0.035		-0.228*	
	(0.040)		(0.127)	
reduction	-0.076*		-0.128	
	(0.043)		(0.182)	
*priv*replacement*	-0.191		-0.396	
	(0.157)		(0.471)	
*priv*enlargement*	-0.329**		0.996**	
	(0.136)		(0.404)	
*priv*reduction*	-0.056		1.769**	
	(0.165)		(0.706)	
number replacement		0.006		0.029
		(0.031)		(0.112)
number enlargement		0.053		-0.221
		(0.036)		(0.139)
number reduction		-0.089**		-0.051
		(0.037)		(0.151)
*priv*number replacement*		-0.134*		-0.099
		(0.077)		(0.210)
*priv*number enlargement*		-0.278***		0.784**
		(0.103)		(0.306)
*private*number reduction*		0.017		1.070**
		(0.101)		(0.542)
log(number team)	-0.031	-0.033	0.159*	0.155*
	(0.028)	(0.028)	(0.083)	(0.082)
m_graduate	-0.029	-0.025	0.017	0.024
	(0.036)	(0.036)	(0.095)	(0.095)
m_technical	0.025	0.024	-0.102	-0.098
	(0.030)	(0.030)	(0.086)	(0.086)
m_indexp	-0.019	-0.022	-0.066	-0.057
	(0.041)	(0.041)	(0.100)	(0.100)

(To be continued on next page)

Model	Growth		Δ Labor productivity	
	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)
m_ majority	-0.033	-0.034	0.018	0.014
	(0.037)	(0.037)	(0.084)	(0.084)
good rating	-0.079	-0.082	-0.154	-0.168
	(0.056)	(0.056)	(0.135)	(0.132)
medium rating	-0.083	-0.084*	-0.050	-0.058
	(0.051)	(0.051)	(0.129)	(0.127)
cont. R&D	0.052	0.048	0.057	0.057
	(0.033)	(0.033)	(0.090)	(0.089)
log(firm age)	-0.014**	-0.014**	-0.069***	-0.068***
	(0.007)	(0.007)	(0.022)	(0.022)
log(initial size)	0.003	0.003		
	(0.008)	(0.008)		
log(labor productivity$_0$*)*			-0.674***	-0.678***
			(0.061)	(0.061)
East Germany	-0.007	-0.008	-0.268**	-0.273**
	(0.038)	(0.038)	(0.116)	(0.115)
constant	0.348***	0.351***	-0.724***	-0.733***
	(0.077)	(0.076)	(0.211)	(0.209)
industry dummies	included	included	included	included
log likelihood	-203.27	-200.37	-652.34	-652.38
F(all)	1.76**	2.20***	9.86***	36.64***
F(industries)	1.97*	1.89	2.47**	2.50**
Adjusted R^2	0.029	0.038	0.250	0.250
BIC	-3,196.31	-3,202.11	-1,695.57	-1,695.47
number of observations	588	588	505	505

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of OLS estimations on changes in firm growth and labor productivity. Robust standard Errors are in parentheses.
[a] Variables indicating that occurred previous to the observation time of the dependent variable.
[b] F(all) displays an F-test of the joint significance of all variables.
[c] F(industries) displays an F-test of the joint significance of industry dummies.

3.4.4. Concluding remarks

This chapter investigates the determinants and the timing of changes within the initial top management team in young high-tech firms. We take several factors into account: VC financing, characteristics of the initial top management team and other firm characteristics. Finally, we investigate the effects of changes and VC-induced changes on firm performance – measured by firm growth and labor productivity. As far as we are able to, the selectivity of VC financing is controlled for.

Confirmation of the anecdotic evidence that VC investors are particularly impatient and push relatively early for replacement of the initial top management team is found. But if we control for the selection process underlying VC investment activities the effects on replacement vanish. Hence, the positive correlation between VC investment and replacement can be attributed to the high selectivity of VC investors but is no causal effect. Obviously, firms self-select in VC financing if they are more prone towards changes. Or taking it the other way around, VCCs select firms in which changes in the top management are more easily enforceable.

If more objective measures like performance figures are looked at effects of VC-financing can be found. Particularly for labor productivity, the return-oriented private VCCs have a positive impact specifically via inducing changes in the executive teams. For the growth equation, the disentangled effects of VC- and non-VC-induced changes also have impacts on performance. Negative effects of VC interventions in the top management can be found. Those effects can be explained by the previously bad performance which may have led to changes in the executive team. This effect may not have been compensated until the time of performance measurement. If we account for the separated effects of VC involvement, we can confirm a positive effect of VC investment if the firms had not experienced a change in the top management. This effect is even stronger for private VCCs. Hence, other dimensions of active involvement beyond changes in the top management contribute positively to firm growth.

In a nutshell, although the impact of active investors on changes is revealed to be a selection effect, their involvement in the firm even in its strongest manifestation, namely changes in the top management, influences performance. In the case of labor productivity, this effect is positive. For the growth figure, we confirm a negative effect.

3.5. Innovation and Venture Capital financing

3.5.1. Hypotheses

This section investigates the impact of VC financing on firms' innovation activities. This is motivated by the observation that many of today's global players in innovative markets have been VC-funded at the beginning. Famous examples for the U.S. are Apple, Microsoft and Genentech. This anecdotic evidence is also confirmed by the literature (see Section 3.2.2.2). This section concentrates on entrepreneurial firms in German high-tech sectors and tries to find out whether the findings of previous literature can be confirmed in this context.

The first hypothesis is based on the results of Kortum and Lerner (1998, 2000) as discussed in Section 3.2.2.2. They find a positive effect of VC investments on patenting behavior at the industry level. This section tests whether this link also holds for the firm-level focusing on German high-tech entrepreneurial companies.

Hypothesis 1: *Venture Capital spurs innovation proxied by firm's patenting behavior.*

Griliches, Pakes and Hall (1987) describe some problems that arise when relying on patents as indicators for innovative activities. First, patents differ in size and/or value. Second, the output of R&D activities is only represented in fraction by patents since not all R&D activities are patentable or patented. Furthermore, the fraction patented may also vary over industry, firm and time.

When a firm has successfully innovated, it can decide to use either secrecy or patenting to protect their findings and appropriate the returns of its innovative activities. Patents are an instrument to protect innovation in that they legally generate a temporary monopoly on the intellectual property. But patenting may have a large strategic component, e.g. bargaining power, cross-licensing and reputation (Cohen et al. (2000)). Furthermore, patenting involves the disclosure of newly generated knowledge, technologies or processes which may alleviate imitation (Anton, Yao (2004)).

Additionally, Kortum and Lerner (2000) point out that venture capital may spur patenting while having no impact on innovation. First, patents may serve as a signal for firm's quality to potential VC investors, i.e. patents may help to attract VC with the consequence that firms wishing to get VC are more prone to patent their invention. Second, patents are used as a protection mechanism against expropriation of the entrepreneur's ideas by the VCs. Kortum and Lerner account for patent quality by using several quality measures. Hence, it would be worthwhile to control for the quality of the patents. A caveat of quality measures is that they are strongly right-censored since future citations and litigations cannot be detected. In the case of very young firms – like in this data set – the right-censoring deteriorates these measures because most patents were only recently filed.

But the data set provides a categorical indicator of firm's innovativeness, i.e. whether the innovative activity that results in totally new methods and technologies is done mainly by the firm itself or by a third party, or whether the innovative activity results in a new combination of tried and tested methods and technologies (for a more detailed variable description, see Table 3.22 on page 122 and Appendix B.3) on pp. 217. With this variable we are able to show the effects of VC financing on the result of innovative activity. Since VC companies are often perceived to concentrate on industries which are characterized by a high innovative potential, we conjecture that VC-backed firms are characterized by a higher probability to develop the totally new methods and/or technologies themselves.

Hypothesis 2: Firms are more likely to develop the methods and technologies, they use to build their products, themselves if they are VC-backed.

3.5.2. Descriptive statistics

The basis of the empirical analysis is the ZEW-HF06 described in Section 3.3 and in Appendix B.2. To this data set we merge patent information from the PATSTAT data set up to the year 2006 in order to capture the innovative output of the firms. PATSTAT is the abbreviation of "EPO Wordwide Patent Statistical Database" created by the European Patent Office (EPO) which has been requested by the Patent Statistics Task Force led by the OECD. PATSTAT includes patent information from 73 patent offices all over the world and is designed for serving statistical purposes.

We concentrate on European and German priorities, e.g. patents filed at the German Patent and Trademark Office (Deutsches Patent- und Markenamt – DPMA) or at the EPO for the first time. If combining different patent information sources, as it is the case for the PATSTAT data, it is possible that several entries are found for one patent, a so-called patent family. For example, firms may file a patent at the DPMA, and some time later they apply at the EPO for the same invention, e.g. to get a geographically more expanded protection, or because the fees at the patent offices differ. In order to avoid "double entries", i.e. double counts of the same patented invention, we trace back all priorities found for one patent until we have found the first European or German priority. The routine which helps us to go back within the priority trees provided by PATSTAT was implemented by Thorsten Doherr. Patents are then clustered for the first priority so that in the end we have assignments of patents to firms avoiding double entries.

The merge to the survey data set is done using a computer-assisted string search (see Section 3.3.1) in the applicant variable. We have only searched the applicants because we focus on those firms having the right to use the intellectual property. Since the firms in the data set are relatively young and small, we have searched for the firm names as well as the names of firms' executives. Regarding the search for executives names, we assume that the firm is allowed to use patents filed by its executives.

By aggregating patents to one number for every firm from firm foundation, we may run into the problem of timing. The aim of this study is to identify the impact of VC financing on innovation. Since VC funding often occurs some time after firm foundation concerns may arise concerning timing. Patenting may happen before VC entry. A closer look at the data, instead, reveals that apart of two exceptions patenting took place after VC entry, i.e. two patents have been filed before VC entry. Hence, the timing problem is not that pronounced.

Furthermore, additional data taken from the ZEW Foundation Panel (Creditreform data) is linked so that information on stakeholders, location and rating is added. Finally, indications for the distances of the firm to universities and public research institutions has been appended by linking firm location with the location of research facilities. The calculation of the distances has been done by linking the centers of the respective ZIP code areas. For the regressions, the distance to the closest research institution – either university or public research facility – is included which should account for possible spillovers.

Table 3.21 lists all variables used throughout the regressions and Table 3.23 depicts the respective descriptive statistics of the variables included in the regressions below. Two different dependent variables are used to test the hypotheses: the number of patents

Table 3.21.: Variables description for the link of VC financing and innovation

Variable name	Type	Description
Dependent variables		
patents_ after	integer	Patents filed after firm foundation
innovativeness	categorical	Degree of innovativeness of the most important product
Explanatory variables		
venture capital	indicator	Venture capital financing
private vc	indicator	Investment of a private VC company
continuous R&D	indicator	continuous R&D activities
patent_ before	indicator	use of patents filed before firm foundation
m_ graduate	indicator	University degree or PhD: highest degree in founding team
m_ technical	indicator	Highest degree in founding team: predominantly technical
m_ majority	indicator	majority stake held by executives at firm foundation
log(initial size)	continuous	logarithm of number of employees at firm foundation
good rating	indicator	good initial rating
medium rating	indicator	medium initial rating
log(distance)	continuous	logarithm of the distance to the closest research facility
East Germany	indicator	firm is located in East Germany

applied after firm foundation and innovativeness (see Table 3.22 and Appendix B.3 for a detailed description of this variable). The average firm has applied for 0.41 patents after firm foundation (*patents_ after*). The fractions of the different categories of innovativeness (*innovativeness*) are displayed in Table 3.22. New methods and technologies used to build the top-selling product are developed in almost 43 % of the firms themselves. 27 % use new methods and technologies developed by another firm and over 17 % use an innovative combination of tried and tested methods and technologies. Almost 13 % of the cases by the firms employ a known combination of tried and tested methods and technologies, and hence, are not innovative. The question was designed to represent product as well as process innovation. In the ZEW-HF06, the question about the innovativeness only asks about the top-selling product. Obviously, there is a difference between a product and a firm, since a company may build several products. That means that a firm may indicate that their top-selling product is not innovative, although the firm may be innovative, and perhaps use the return of the top-selling good to "subsidize" the innovation activities. This problem cannot be solved since the data has been collected as such. But small firms usually produce a quite small number of products, particularly if they are young, so that this issue should not be severe.

For testing the hypotheses, the variable *venture capital* is included in the regressions. In the data set on high-tech entrepreneurship, almost 8 % of the firms are VC-backed. This dummy variable indicates whether the firm has received venture capital financing. There may be two reasons why VC funding may have an impact on the propensity to patent. A positive effect of VC funding would suggest that it enables the entrepreneur to increase the intensity of researching: First, it rises the amount of financial resources and the firm may thus bridge its funding gap. Second, VC financing is assumed to provide support beyond financing, and may hence render the firms more productive. To disentangle the financing and the value added effect, we run two robustness checks: In alternative regressions, we include an indicator regarding the type of VC investor. As private VC companies, like independent VCCs (e.g. 3i), corporate VCCs and bank VCCs, are supposed to be focused on return and usually on a relatively narrowly defined technology field for which they have built up expertise, i.e. they may be able to provide substantial knowledge from which the firm can benefit. Therefore, private VC funding should supply more assistance to the firms than public VCCs (MBGs, tbg, state and savings banks) whose primary goal is to foster employment growth, specific regions or industries (see also Section 3.4.2). A second robustness check is run by relating the average number of patents per year to VC financing. This should reveal whether VC-backed firms are more productive in terms of patents. The average firm files 0.09 patents per year whereas the maximum number is 8.

One input factor of the innovation process are R&D activities, usually, reflected as R&D expenditures. Unfortunately, these are not included in the data set. Alternatively, we could rely on R&D employees as a measure for R&D activities which are closely linked to R&D expenditures. But we only have information on the number of R&D employees for the year 2005. As we look at patents since firm foundation, this will cause timing problems. Therefore, we use a dummy variable, called *continuous R&D* which reflects whether firms continuously conduct research and development activities. The question reflects the whole period since firm foundation. One third of the firms in the data set are continuously involved in R&D activities.

Table 3.22.: Characteristics of the variable *innovativeness*

cat.	The product is characterized by...	Fraction
3	...new methods and technologies developed by the firm itself	46.7%
2	...new methods and technologies developed by a third party	25.0 %
1	...a new combination of tried and tested methods and technologies	16.3 %
0	...a known combination of tried and tested methods and technologies	12.0 %

The characteristics of the founding management team are crucial for young firms, e.g. they may mainly determine the absorptive capacity of the firm, in particular, during the first years, so that we include indicators regarding prior knowledge and experience of the founding team which are assumed to influence the identification, assimilation and exploitation of external knowledge, e.g. generated by research facilities (Cohen, Levinthal (1989)). Therefore, we account for the educational background. The variables regarding the management team (*m_*) reflect the situation for the founding management team. Technological experience usually plays a substantial role in current innovation activities. Thus, variables reflecting the educational background and experience of the founding management team are included. First, the experience is represented by the dummy *m_graduate* reflecting that at least one manager holds a PhD or university degree (about 64 % of the firms). Furthermore, almost 60 % of those highest educational degrees are predominantly technical (*m_technical*). Those degrees are not necessarily academic degrees. Furthermore, we take into account whether some patents have been filed before firm foundation to control for patenting experience (*patent_before*). We only include this indicator in the patenting regressions. In the innovativeness regressions, this dummy mainly displays unit value if the firms also state that they use self-developed technologies. This finding is quite intuitive since patents are defined by the newness of the invention. An externally developed technology is new but the property right should belong to the other party, and innovative combinations may not be new enough to be patented.

Table 3.23.: Descriptive statistics for the link between VC financing and innovative activities (both models)

Variable	Mean	Std.Dev.	Min	Max
Dependent variables				
patents_ after	0.409	1.629	0	15
innovativeness	1.995	1.059	0	3
Explanatory variables				
venture capital	0.077	0.266	0	1
private vc	0.040	0.195	0	1
continuous R&D	0.334	0.472	0	1
patent_ before	0.041	0.198	0	1
m_ graduate [a]	0.637	0.481	0	1
m_ technical [a]	0.595	0.491	0	1
m_ majority [a]	0.276	0.447	0	1
initial size [a]	4,365	4,935	0.5	38
good rating [a]	0.295	0.456	0	1
medium rating [a]	0.566	0.496	0	1
distance	14.366	15.547	0.100	94.801
East Germany	0.159	0.366	0	1
Number of observations		885		

[a] Variables displaying status at firm foundation.

Moreover, we account for ownership structure, i.e. separation of ownership and control which may influence risk exposure. Thus, we include *m_ majority* which has unit value if the management held majority stake at firm foundation. Over one fourth of the firms are managed by executives holding majority stake. According to the principle agency theory, managers who do not own the firm may act in a way that serves themselves and not the firm, e.g. they could be reluctant to invest in risky projects like innovation projects because they may be fired in case of failure. Furthermore, we include two indicators concerning the credit rating index reflecting a *good* and a *medium rating.* The rating is supposed to display firms' exposure, to approximate the riskiness of the firm, and to influence the business relations, particularly the access to debt markets. As a result, good ratings are conjectured to have a positive effect. The exact definition of the rating indicators can be found in Section 3.3.2.

Typical firm characteristics linked to innovation activities are firm size which is included as the logarithm of the number of employees at the founding date (*initial size*). The average firm has 4.4 employees at firm foundation. Furthermore, foundation year dummies are included to reflect the different starting conditions of the firms. The firms have been founded during a observation period, in which the German high-tech sectors have experienced an extraordinary boom period from 1997 until the beginning of 2000 and a downturn period afterwards. Finally, industry dummies (*high-tech 1, high-tech 2, hardware, software*) are also included. Moreover, innovation often depends on spillover effects, in that firm may benefit from specific research facilities. In order to account for such effects, the distance to universities or public research facilities (*log(distance)*) is included in the regressions.

3.5.3. Empirical methodologies

3.5.3.1. Patents as Innovation Indicator

To investigate the impact of VC financing on patenting we use count data models because the patent information displays the typical characteristics of a count process: It contains many zeros and is of discrete nature whereas many observations have only small values (Greene, 2003, Winkelmann, 1994). It would be desirable to estimate this issue by using panel data and to rely, for example, on the linear dynamic feedback model presented in Blundell et al. (1995). They state that unobservable permanent heterogeneity is an important feature of empirical models of innovation. They propose a dynamic count data model with fixed effects in which the fixed effects are approximated by information of pre-sample periods. They state that a long history of the dependent variable is needed. A common approach is to include the logs of patents from a pre-sample period in a standard pooled cross-sectional count model (for an application see Czarnitzki et al. (2008)). Since in many studies evidence is found which hints at the importance of innovation experience for patenting activities we should take this into account. By construction, the pre-sample information on which we could rely would be the period before foundation. Thus, the only possibility to account for pre-sample patenting would be to count patents filed by the executives of the entrepreneurial firms. This procedure is likely to create a spurious measure of the pre-sample patenting which the firms are able to use. The only measure we can rely on is an indicator of whether the firm uses patents which have been filed before firm foundation. This measure is included in the ZEW-HF06 and reflects for which firms' innovation experience dating back to pre-foundation is decisive for firms' innovation activity.

It would be possible to construct a panel data set but the only variable which varies over time is the number of patents all other variables are not time-varying[31]. Therefore, we stick to cross-sectional estimation tools controlling to a certain extent for heterogeneity in patenting experience by including the dummy *patent_ before*.

The patent variable consists of many zero counts: Over 75% of the firms report that they do not make use of own patents, i.e. the patent variable exhibits excess zeros. According to Blundell et al. (1995) firm specific heterogeneity in cross-section data is reflected in a larger number of zero outcomes than the standard count models would predict, therefore methods should be used that account for those excess zeros. A common method is to use a regression method accounting for the generation of the zeros. Two models may be applicable with excess zeros: the hurdle and the zero-inflated model.

The hurdle model changes the probability of the zero outcome and scales the remaining probabilities. It also determines with the aid of a binary probability model, for example a probit or logit model, whether a zero or a nonzero outcome occurs. The positive outcomes of the count variable are modeled using a "truncated" Poisson or Negative Binomial model. The underlying assumption is that all observations are potentially innovative and could file patents (Mullahy, 1986, Greene, 2003, pp. 749-752).

An extension of the hurdle model is a zero-inflated model (see Lambert, 1992) in which two different regimes are supposed to generate zero outcomes. In one regime, the outcome is always zero (*regime1*) and in the other regime the zeros stem from a usual Poisson process which includes zeros as well (*regime2*) so that

$$Prob(y_i = 0|x_i) = Prob(y_i = 0|regime1) + Prob(y_i = 0|x_i, regime2)Prob(regime2).$$

[31] For few firms, the VC dummy jumps from zero to one and then remains in this state since in general we do not observe VC exit.

In the patent case, the zero-inflated model is preferred because the zero patents may stem from two different sources: First, the firm is not innovative, and thus, will never file a patent (*regime1*), and second, the firm is innovative but has not filed a patent because either the outcome of the innovation process is not (yet) patentable or the firm has decided to keep the knowledge secret (*regime2*). In the context of the underlying data set, one might argue that all high-tech firms are potential innovators so that regime 1 does not occur and a hurdle model would be appropriate. But the definition of high-tech firms is based on the industry-level and considers the industry R&D intensity, i.e. it is probable that the data set includes firms which belong to *regime 1*.

The intuition of the zero-inflated models is to estimate a binary probability model for which the indicator is one if the zero outcome stems from the usual Poisson process (regime2) and zero if it is always zero (regime1). The zero-inflated models can be described as follows (Cameron and Trivedi, 1998, pp.125-128):

$$Pr(y_i = 0) = \varphi_i + (1 - \varphi_i)e^{-\mu_i}.$$

For Poisson:

$$Pr(y_i = r) = (1 - \varphi_i)\frac{e^{-\mu_i}\mu_i^r}{r!}$$

For Negbin:

$$Pr(y_i = r) = (1 - \varphi_i)\frac{\Gamma(r + \alpha^{-1})}{\Gamma(r + 1)\Gamma(\alpha^(- 1))}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\alpha^{-1} + \mu}\right)^r,$$

with r=1,2,... and r is the realized count of firm i's patents (y_i). It is assumed that the proportion of zeros, φ_i, follows a logistic function, so that

$$\begin{aligned} y_i &= 0 \; with \; probability \; \varphi_i \\ y_i &\sim Po(\mu_i) \; with \; probability \; (1 - \varphi_i), \end{aligned}$$

$$\text{with } \varphi_i = \frac{exp(z_i^{'}\gamma)}{1+exp(z_i^{'}\gamma)}.$$

The zero-inflated Poisson model is overdispersed. This overdispersion partly results from the nature of the zero-generating process. But it may also stem from heterogeneity which cannot be captured by the Poisson model. In order to identify whether a Poisson or a Negbin model is the appropriate model we perform an LR-test of $\alpha = 0$, whereas α is the dispersion parameter. Additionally, we perform a test to demonstrate whether the zero-inflated version of the count data model is to be preferred, i.e. we test whether there is a significant difference between the zero-inflated model and its non-zero-inflated counterpart. For that, Vuong (1989) proposes a likelihood-ratio test for non-nested models. Let $f_j(y_i|x_i)$ be the predicted probability that the count is y_i under the assumption that the distribution is $f_j(y_i|x_i)$ for the models $j = 1, 2$ and $m_i = log\left(\frac{f_1(y_i|x_i)}{f_2(y_i|x_i)}\right)$ then the test statistic for model 1 versus model 2 is

$$v = \frac{\sqrt{n}\left[\frac{1}{n}\sum_{i=1}^{n} m_i\right]}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_i - m)^2}}$$

The limiting distribution of the test statistic is standard normal. The results of the Vuong test in Table 3.24 indicate that the zero-inflated models better fit the data than the non-zero-inflated versions.

3.5.3.2. Innovativeness

Since innovativeness is measured as a categorical variable with four exclusive categories, we estimate a multinomial logit model. The standard starting point for discrete choice models is the latent regression where we only observe the discrete variable y consisting of four categories (here: innovativeness as described in Table 3.22 and Appendix B.3). The results of the multinomial logit are interpreted as odd ratios due to the normalization. An important property of the multinomial logit is the so-called independence from irrelevant alternatives (IIA) assumption which is tested with the Hausman specification test. See Section 3.4.3.1 for a more detailed description of the multinomial logit.

3.5.4. Empirical Results

Table 3.24 depicts the results for a zero-inflated Poisson model with robust standard errors and a zero-inflated Negative Binomial model. First looking at the bottom of Table 3.24 the Vuong test for the ZINB and the ZIP confirms that the zero-inflated versions of count data indeed fits the data better than the non-zero-inflated ones. Furthermore, the χ^2-test that the variance parameter α equals zero can clearly be rejected. As a consequence, the model that best fits the data is the zero-inflated negative binomial count data model. We choose a logit type model to represent the zero outcomes.

Table 3.24 displays the unconditional marginal effects of the count models, i.e. taking account of the process determining the zero outcomes. The marginal effects are calculated at the sample means. The standard errors of the marginal effects are transformed using the delta method. The results show that venture capital funding has a positive impact on patenting, i.e. the effect of VC-backing increases the expected number of patents. This effect confirms Hypothesis 1 that VC financing spurs firms' patenting activities. For our first robustness check, we estimate the same equation with the private VC dummy in order to test whether the VC effect can be attributed to the active involvement of the VC investor. This effect turns out to be insignificant. Hence, there is no effect of private VC funding compared to non-private VC funding. This result does not necessarily mean that private VCCs and consequently active involvement have no impact on firms' innovation activities. First, because the reference group may be a mixture of non-VC-funded, public VC-funded and non-detected private VC-funded firms. Second, we observe firms relatively early in their lifecycle, and thus our patenting variable is most probably censored. The censoring occurs because we are not able to capture future patenting. Our second robustness check relates VC financing to the average number of patents per year (see Table B.8 on page 222 in the Appendix). VC financing has a positive impact on the average number of patent applications per year. This result holds if we estimate the same model for private VCCs as well as for the selectivity of VC investment. Hence, VC funding makes the firms more productive in terms of patents, which strengthens the previous results.

We can also confirm that previous experience in patenting spurs current patenting activities. This is in line with the findings of Blundell et al. (1995) and Czarnitzki et al. (2008). Furthermore, continuous R&D activities also increase the probability of firms' patenting. This result is not surprising since R&D is an input factor of the

Table 3.24.: Unconditional marginal effects of zero-inflated count data models regarding patenting activities

Model	ZIP		ZINB	
	Marg.Eff. (Std.Err.)	Marg.Eff. (Std.Err.)	Marg.Eff. (Std.Err.)	Marg.Eff. (Std.Err.)
venture capital	0.421** (0.208)		0.273* (0.145)	
private vc		0.564* (0.316)		0.233 (0.183)
cont. R&D	0.468*** (0.104)	0.501*** (0.105)	0.406*** (0.097)	0.378*** (0.094)
patent_before	0.049 (0.061)	0.026 (0.051)	1.173** (0.552)	1.284** (0.602)
m_graduate	0.030 (0.062)	0.024 (0.063)	0.099* (0.054)	0.114** (0.058)
m_technical	0.008 (0.048)	0.017 (0.045)	-0.000 (0.054)	0.011 (0.055)
m_majority	0.006 (0.039)	0.021 (0.041)	0.038 (0.051)	0.040 (0.054)
log(initial size)	0.064** (0.027)	0.069** (0.028)	0.055* (0.031)	0.060* (0.032)
good rating	-0.087* (0.045)	-0.087* (0.046)	-0.079 (0.056)	-0.079 (0.061)
medium rating	-0.103* (0.054)	-0.080 (0.053)	-0.066 (0.065)	-0.069 (0.068)
log(distance)	0.006 (0.011)	-0.000 (0.011)	0.008 (0.014)	-0.002 (0.013)
East Germany	0.044 (0.064)	0.068 (0.068)	-0.035 (0.050)	-0.030 (0.055)
industry dummies	included	included	included	included
foundation years	included	included	included	included
α			2.102 (0.588)	2.404 (0.688)
log Likelihood	-470.52	-468.41	-419.45	-423.10
Vuong test	4.11***	4.13***	3.98***	4.37***
LR test ($\alpha = 0$)			102.13***	90.63***
χ^2 *(all)* [a]	104.06***	114.51***	94.60***	94.82***
χ^2 *(industries)* [b]	6.92*	7.75*	6.55*	6.25***
χ^2 *(foundation years)* [b]	31.02***	27.98***	40.14***	40.60***
McFadden's R^2	0.175	0.178	0.186	0.179
McFadden's adjusted R^2	0.112	0.116	0.114	0.107
Cragg-Uhler's R^2	0.279	0.284	0.283	0.273
BIC	-4,819.93	-4,824.14	-4915.27	-4,907.98
Number of observations	885	885	885	885

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the unconditional marginal effects calculated at the sample means of a zero-inflated Poisson with robust standard errors and Negative Binomial models. Marginal effects of dummy variables are interpreted as discrete change from 0 to 1. Standard Errors are obtained by using the delta method.

[a] χ^2(all) displays an χ^2-test of the joint significance of all variables.

[b] χ^2(industries) and χ^2(foundation years) display χ^2-tests on the joint significance of industry and foundation year dummies. Four industry dummies for high-tech 1, high-tech 2, hardware and software are included.

innovation process, and hence increases the inclination to patent its outcome and to appropriate the returns on R&D activities. Regarding the management team, a positive impact can be found for firms with at least one top manager holding a university degree showing that absorptive capacities, particularly of the executives, are crucial for young high-tech firms' innovation activities. And finally, firms patenting behavior is positively influenced by the initial size of the firm.

Table 3.25 depicts the results of the multinomial logit estimation where the effects of VC financing on the degree of innovativeness are tested. The base category is "known combinations of tried and tested methods". The Hausman test confirms that the IIA holds in our regressions, i.e. the results for one category of the dependent variable is independent of leaving out alternatives, and hence the multinomial logit regression can be used to assess the hypotheses regarding innovativeness.

VC financing as hypothesized has a positive effect on the probability that firms develop the new methods and technologies themselves with respect to using known combinations of established methods and technologies. The probability increases by 27 percentage points. Furthermore, VC- backed firms are less inclined to use methods and technologies developed by others or innovative combinations with respect to known combinations of tried and tested technologies. For firms funded by private VC companies (see Table 3.26), we confirm a positive effect on using self-developed new technologies and a negative impact on using new technologies developed by other firms with respect to being non-innovative.

For continuous R&D activities, we find a positive effect on the probability of using self-developed technologies and negative ones regarding both innovative combinations of tried and tested technologies and new technologies developed by others. The positive effect on self-developed technologies is as expected. The negative effects can be explained by the fact that continuous R&D activities may be obsolete if a firm uses new technologies developed by others.

Looking at the educational background, the use of new self-developed technologies with respect to non-innovative combinations of tried and tested technologies is favored by firms the top management of which is characterized by at least a university degree. Teams in which no university degree is present have a higher probability of using new technologies developed by other firms. If there is no academic degree, firms are prone to buy the cutting-edge technology developed by other firms. These findings suggest the importance of absorptive capacities in the top management team for the innovation process in young and small high-tech firms.

Good and medium initial rating have positive effects on the probability of using new technologies developed by other firms which is quite intuitive because in this case business relations need to be established which may be based on the rating score. We find a negative link between medium rating with respect to a bad rating. This effect reflects that firms which are initially riskier display a higher probability to use new self-developed technologies. Finally, we find a negative effect on using new technologies developed by other firms if the entrepreneurial team holds majority stake at foundation. This may be a hint that manager-led firms in which the separation of ownership and control prevails are reluctant to take high risks and hence instead of developing the new technologies themselves they buy the new technologies developed by others.

3.5.5. Endogeneity of venture financing

The previous section suggests that the impact of VC on patenting and innovativeness is positively significant. However, some concerns about the binary variable *venture capital* exists which have already been denoted in the literature review in Section 3.2.2.2. Particularly, in the context of patenting, Kortum and Lerner (2000) state that patents may serve as a signal of firm's quality to potential VC investors, i.e. patents may help to attract VC with the consequence that firms wishing to get VC are more prone to patent their invention.

Thus, endogeneity arises in the context of patenting and innovativeness because it is not clear whether the firm is innovative because it is able to bridge the funding gap by receiving venture capital or whether VC companies select firms which have a high probability to be innovative. In line with the selection argument is the fact that preceding VC investments a due diligence process takes place which strongly influences the VC decision regarding investment opportunities. This argumentation resembles very much a selection problem, i.e. receiving VC financing is not random. Furthermore, endogeneity may arise because of the existence of variables that are correlated with innovative activities – both patenting and innovativeness – and VC financing. Such factors can be observable, like the educational background or professional experience

Table 3.25.: Marginal effects for multinomial logit regarding firms' innovativeness

Model	self	other	inno
	Marg.Eff. (Std.Err.)	**Marg.Eff. (Std.Err.)**	**Marg.Eff. (Std.Err.)**
venture capital	0.276***	-0.208***	-0.086**
	(0.071)	(0.041)	(0.044)
cont. R&D	0.422***	-0.180***	-0.114***
	(0.035)	(0.030)	(0.026)
m_graduate	0.153***	-0.135***	-0.012
	(0.042)	(0.037)	(0.031)
m_technical	0.067*	-0.011	0.023
	(0.040)	(0.033)	(0.028)
log(initial size)	0.036	-0.013	-0.014
	(0.024)	(0.020)	(0.017)
good rating	-0.049	0.096	-0.044
	(0.063)	(0.061)	(0.040)
medium rating	-0.061	0.096*	-0.060
	(0.057)	(0.050)	(0.041)
m_majority	0.045	-0.076**	0.018
	(0.043)	(0.034)	(0.032)
log(distance)	0.009	-0.006	-0.003
	(0.011)	(0.009)	(0.008)
East Germany	-0.082	0.077	0.033
	(0.052)	(0.050)	(0.042)
industry dummies		included	
foundation years		included	
log Likelihood		-1,003.48	
χ^2 *(all)* [a]		270.85***	
χ^2 *(industries)* [b]		12.28	
χ^2 *(foundation years)* [b]		16.65	
McFadden's R^2		0.119	
McFadden's adjusted R^2		0.064	
Cragg-Uhler's R^2		0.285	
BIC		-3,586.23	
Number of observations		887	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the marginal effects of a multinomial logit model for *self*-developed, externally developed (*other*) new technologies and *inno*vative combinations of tried and tested technologies. The base category is known combinations of tried and tested technologies. The marginal effects are calculated at the sample means, standard errors are transformed using the delta method. The Hausman test indicates that the IIA holds.

[a] χ^2(all) displays an F-test of the joint significance of all variables

[b] χ^2(industries) and χ^2(foundation years) display χ^2-tests on the joint significance of industry and foundation year dummies. Four industry dummies for high-tech 1, high-tech 2, hardware and software are included.

Table 3.26.: Marginal effects for multinomial logit regarding firms' innovativeness (private VC)

Model	self	other	inno
	Marg.Eff. (Std.Err.)	Marg.Eff. (Std.Err.)	Marg.Eff. (Std.Err.)
private vc	0.296***	-0.190***	-0.128***
	(0.090)	(0.056)	(0.044)
cont. R&D	0.429***	-0.187***	-0.115***
	(0.034)	(0.030)	(0.025)
m_graduate	0.156***	-0.141***	-0.010
	(0.042)	(0.037)	(0.030)
m_technical	0.068*	-0.012	0.022
	(0.039)	(0.033)	(0.028)
log(initial size)	0.038	-0.014	-0.015
	(0.024)	(0.020)	(0.017)
good rating	-0.036	0.087	-0.048
	(0.063)	(0.061)	(0.039)
medium rating	-0.057	0.093*	-0.062
	(0.057)	(0.051)	(0.041)
m_majority	0.045	-0.075**	0.017
	(0.043)	(0.034)	(0.031)
log(distance)	0.006	-0.004	-0.002
	(0.011)	(0.009)	(0.008)
East Germany	-0.071	0.068	0.030
	(0.052)	(0.050)	(0.041)
industry dummies		included	
foundation years		included	
log Likelihood		-1,006.88	
χ^2*(all)* [a]		264.04***	
χ^2*(industries)* [b]		12.12	
χ^2*(foundation years)* [b]		16.77	
McFadden's R^2		0.116	
McFadden's adjusted R^2		0.061	
Cragg-Uhler's R^2		0.279	
BIC		-3,579.42	
Number of observations		887	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the marginal effects of a multinomial logit model for *self*-developed, externally developed (*other*) new technologies and *inno*vative combinations of tried and tested technologies. The base category is known combinations of tried and tested technologies. The marginal effects are calculated at the sample means, standard errors are transformed using the delta method. The Hausman test indicates that the IIA holds.

[a] χ^2(all) displays an F-test of the joint significance of all variables

[b] χ^2(industries) and χ^2(foundation years) display χ^2-tests on the joint significance of industry and foundation year dummies. Four industry dummies for high-tech 1, high-tech 2, hardware and software are included.

of the top managers, or unobservable, like the quality of the innovative idea, prototype or new product.

In order to account for endogeneity, we estimate an IV equation in both models. For identification reasons, this equation is specified using additional regressors, i.e. instrumental variables, that influence the probability of VC financing but not the patenting or innovative behavior. We use four variables in the VC equation which reflect firm risk and may be used by the VC investor to assess and evaluate this risk. First, we control for the number of the founding team members (*team*); the higher the number of team members the more probable the necessary abilities and skills, particularly regarding management and marketing, are reflected in the management team and the lower the risk. This reasoning is corroborated by the theoretical work of Lazear (2004) who finds that entrepreneurs or entrepreneurial teams are more generalists with regard to abilities than specialists (jacks-of-all-trades). Hence, starting a business requires a balanced skill portfolio. In this respect, building up entrepreneurial teams may be necessary to cope with the relevant portfolio of abilities, i.e. teams in which the skills of all members should be complementary to each other "building" a generalist entrepreneurial team. In line with this argument, we further include an indicator showing whether at least one member of the initial management team has previous industry experience either as an employee or as an entrepreneur (*m_indexp*). This variable also reflects that some abilities are available in the team which can only be achieved by working in an enterprize or founding a firm and which cannot be learned otherwise.

Furthermore, patents filed before firm foundation (*patent_before*) may signal the firm's quality and prove that the project of the firm has a potential to get commercialized and to generate profits within short time. This variable is included as an instrument for the estimation of innovativeness. In the patent equation, it is already included in the count process so that this variable is not an instrument in the IV equation for the count models. Finally, characteristics of the product may also influence the selection of VC investors. We account for *intermediate* products because in this case the customers are a quite clearly cut, mostly small group. Hence, the market potential for this product may be clearer compared to final products. Table 3.27 displays the description and descriptive statistics for the instrumental variables.

In order to account for the endogeneity problem, one may try to estimate both equations sequentially. A natural point to start is to use an IV approach, e.g. a two-stage

Table 3.27.: Description and descriptive statistics for the instruments used in the VC equation to correct for endogeneity

Variable description

Variable name	**Type**	**Description**
team	continuous	number of top managers at firm foundation
m_ indexp	indicator	one manager has industry experience as employee and/or entrepreneur
patent_ before [a]	indicator	firm uses own patents which have been filed before foundation
intermediate	indicator	intermediate product

Descriptive statistics

Variable	**Mean**	**Std.Dev.**	**Min**	**Max**
team	2.046	1.220	1	6
m_ indexp	0.759	0.428	0	1
patent_ before [a]	0.041	0.199	0	1
intermediate	0.405	0.491	0	1

[a] Since we include *patent_ before* in the patenting equations this variable is a “normal” regressor in the IV equation of the count data model. Hence, it is only an instrument in the estimation of the endogeneity-corrected multinomial logit.

estimation in which the first stage estimates the probability for the binary indicator. In the second stage, the fitted values are included and the downward bias of the standard errors is corrected, e.g. by bootstrapping them. Alternatively, a sort of Heckman correction may be plugged in the second stage. However, two-stage estimation procedures can only be applied to linear models. With non-linear estimation procedures – including count and discrete choice models – a two-stage estimation yields inconsistent estimates. Therefore, FIML approaches are used in which the two equations are estimated simultaneously.

3.5.5.1. Patenting activity

Terza (1998) proposes a FIML framework for the estimation of count data model with a binary endogenous regressor. Suppose that the probability density function of the count dependent variable is $f(y|x, d, \epsilon)$, i.e. it depends on the covariates x, the binary (endogenous) variable d and the random (heterogeneity) component ϵ. The switching variable d can be represented by the index function $I(z\alpha + \nu > 0)$.

Conditional on exogenous variables w, ϵ and ν are assumed to be jointly normally distributed with mean vector zero and covariance matrix

$$\Sigma = \begin{pmatrix} \sigma & \sigma\rho \\ \sigma\rho & 1 \end{pmatrix}.$$

The joint conditional density function of y and d given x and z can be written as

$$\begin{aligned} f(y, d|w) &= \int_{-\infty}^{\infty} \Bigg[d \int_{-z\alpha}^{\infty} f(y|w, d = 1, \epsilon) f_{\epsilon\nu}(\epsilon, \nu|w) d\nu \\ &+ (1-d) \int_{-\infty}^{-z\alpha} f(y|w, d = 0, \epsilon) f_{\epsilon\nu}(\epsilon, \nu|w) d\nu \Bigg] d\epsilon, \end{aligned}$$

where $f_{\epsilon\nu}(\epsilon, \nu|w)$ is the bivariate normal of $[\epsilon, \nu]$ conditional on w. This can be rewritten after some reformulations as

$$f(y, d|w) = \int_{-\infty}^{\infty} f(y|x, z, d, \epsilon) \Big[d\Phi^*(\epsilon) + (1-d)\left(1 - \Phi^*(\epsilon)\right) \Big] f_\epsilon(\epsilon|x, z) \tag{3.2}$$
$$\text{with } \Phi^*(\epsilon) = \Phi\left(\frac{z\alpha + (\rho/\sigma)\epsilon}{\sqrt{(1-\rho^2)}} \right).$$

Equation 3.2 cannot be evaluated in closed form. By setting $\xi = \frac{\epsilon}{\sqrt{2\sigma}}$, the joint conditional probability density function of y and d can be approximated by using the Gauss-Hermite quadrature (see Butler and Moffitt (1982)) and is given by

$$f(y_i, d_i|x_i, z_i) = \frac{1}{\sqrt{\pi}} \int_{-\infty}^{\infty} f(y_i|x_i, z_i, d_i, \epsilon) \Big[d_i\Phi_i^*(\epsilon) + (1-d)(1 - \Phi_i^*(\epsilon)) \Big] exp(-\xi^2) d\xi.$$

For Poisson model:

$$f(y_i|x_i, z_i, d_i, \sqrt{2}\sigma\xi) = \frac{exp(x_i\beta + \epsilon)^y exp\big[-exp(x_i\beta + \epsilon)\big]}{y!},$$

For Negbin model:

$$f(y_i|x_i, z_i, d_i, \sqrt{2}\sigma\xi) = \frac{\Gamma(y_i + (1/\alpha))}{\Gamma(1/\alpha)\Gamma(y_i + 1)}\big(\alpha exp(x_i\beta + \epsilon)\big)^{y_i}\big(1 - \alpha exp(x_i\beta + \epsilon)\big)^{(y_i+1/\alpha)},$$

with $\epsilon = \sqrt{2}\sigma\xi$.

Thus, the likelihood function to be estimated with the FIML framework is $\mathcal{L} = \prod_{i=1}^{n} f(y_i, d_i|x_i, z_i)$. This approach does not explicitly account for zero-inflation of patent counts. If this is taken into account the FIML framework must be extended. To our knowledge, there does not exist an estimator accounting for both zero-inflation and endogenous binary regressors. The Poisson version of this estimator has been implemented in STATA (see Miranda (2004)). The Negbin version has been programmed by ourselves based on the program provided by Miranda (2004).

The results of the FIML estimation of the endogenous switching Poisson and Negative Binomial model are presented in Table 3.28. The F-test of joint significance of the instruments is highly significant which is a hint that the instruments are strong. The LR-tests confirm that endogeneity is an issue which has to be taken into account if the impact of VC financing on patent counts is investigated. With respect to VC financing we find that if we control for its endogeneity the positive and significant effect on firms' patenting behavior is confirmed, even in the case of private VC financing (see Table B.9). So that we can confirm our hypothesis regarding the link of VC financing and patenting activities.

Table 3.28.: Results for FIML count data model accounting for endogeneity of VC financing

Model	**Poisson**		**Negative Binomial**	
	Patent equation	**Switching equation**	**Patent equation**	**Switching equation**
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
venture capital	1.395***		0.829***	
	(0.222)		(0.222)	
cont. R&D	2.209***	0.239	2.240***	0.243
	(0.200)	(0.152)	(0.258)	(0.152)
patent_ before	2.864***	0.989***	4.718***	1.025***
	(0.226)	(0.271)	(0.330)	(0.271)
m_ graduate	1.362***	0.522***	0.280	0.508**
	(0.260)	(0.202)	(0.246)	(0.202)
m_ technical	0.438**	0.006	0.148	0.005
	(0.190)	(0.151)	(0.214)	(0.150)
m_ majority	0.746***	-0.247	0.546***	-0.227
	(0.142)	(0.184)	(0.205)	(0.184)
log(initial size)	0.260***	0.087	0.204	0.084
	(0.079)	(0.094)	(0.143)	(0.093)
good rating	-0.895***	0.305	-0.798***	0.298
	(0.212)	(0.250)	(0.272)	(0.250)
medium rating	-0.471**	0.214	-0.572**	0.210
	(0.206)	(0.227)	(0.254)	(0.226)
log(distance)	0.025		0.099**	
	(0.042)		(0.043)	
East Germany	-0.134	0.193	-0.386*	0.183
	(0.184)	(0.179)	(0.219)	(0.179)
log(number team)		0.279*		0.287*
		(0.150)		(0.150)
m_ industry experience		0.160		0.181
		(0.183)		(0.184)
intermediate		0.282*		0.261*
		(0.147)		(0.147)
constant	-5.385***	-2.822***	-4.542***	-2.802***
	(0.463)	(0.414)	(0.532)	(0.413)
industry dummies	included	included	included	included
foundation year dummies	included	included	included	included

(To be continued on next page)

Model	Poisson		Negative Binomial	
	Patent equation	Switching equation	Patent equation	Switching equation
$\hat{\sigma}$	1.904		2.242	
	(0.094)		(0.145)	
$\hat{\rho}$	-0.054		0.143	
	(0.115)		(0.124)	
$\hat{\alpha}$			0.093	
			(0.068)	
Log likelihood	-616.03		-613.78	
LR(endogeneity) [a]	335.96***		322.74***	
χ^2 *(all)* [b]	592.40***		419.02***	
χ^2 *(industries)* [c]	24.15***		13.06	
χ^2 *(foundation years)* [c]	40.59***		57.11***	
χ^2 *(instruments)* [d]	7.95**		7.86**	
McFadden's R^2	0.325		0.254	
McFadden's adjusted R^2	0.273		0.196	
Cragg-Uhler's R^2	0.563		0.450	
BIC	-4,330.70		-4,328.43	
Number of observations	869		869	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts coefficients of an endogenous switching count model which corrects for the endogeneity of the binary variable VC financing in the count models by estimating simultaneously a Poisson (Negbin) model and a probit type VC equation by using a full-information maximum likelihood approach according to Terza (1998). Results for private VCCs can be found in Table B.9 on page 223 in the Appendix.

[a] LR(endogeneity) displays a LR-test of the two models showing that the endogeneity-corrected model is supposed to be the true one. The LR-tests are calculated using the log likelihoods of the standard Poisson and Negbin models.

[b] χ^2(all) displays a test of the joint significance of all variables.

[c] χ^2(industries) and χ^2(foundation years) display tests of the joint significance of industry and foundation year dummies respectively.

[d] χ^2(instruments) displays a test of the joint significance of instrumental variables in the VC equation.

Furthermore, we find a positive effect of using patents which have been filed before foundation. This finding corroborates the fact that experience in patenting has a significant effect on current patenting. We also confirm the positive effect of continuous R&D activities. Furthermore, we find that firms without separation of ownership and control, i.e. their management teams hold majority stake at firm foundation tend to have a higher number of patents. Looking at the effects of initial rating, we detect that initially riskier firms have a higher probability to patent more. Finally, we find a positive effect of the distance to universities or other research facilities which expresses that the longer the distance to the next facility the higher the probability for more patents.

3.5.5.2. Innovativeness

In order to correct for the endogeneity bias in the multinomial regressions, we estimate a FIML model which enables us to correct for this bias. We use an approach proposed by Terza (2002). Section 3.4.3.1 describes this approach in detail.

The results of the endogeneity-corrected multinomial logit are displayed in Table 3.29. Venture capital has still a significantly positive effect on firm's innovativeness particularly on the probability of using new self-developed methods and technologies and on using innovative combinations with respect to using known combinations of tried and tested methods and technologies, so that in this respect hypothesis 2 is confirmed. This result suggests that if the VCC invests the firm is more probably innovative either by self-developing technologies or by using innovative combinations which are presumably combined by the firm itself. The effect on the newness of the product is higher since the difference of the coefficients of newly self-developed technologies and innovative combinations of tried and tested technologies is significant at the 1 % level. Private VCCs (see Table B.10 on page 224 in the Appendix) instead only have a positive effect on the probability of using new self-developed technologies, and a negative one on the probability of using new externally developed technologies. Hence, firms funded by return-oriented private VCCs are less inclined to using new externally developed technologies.

We find positive effects of continuous R&D activities on all degrees of innovation. The effect seems to be larger for self-developed and innovative combinations of tried and tested technologies. The differences with respect to the other categories are significant at the 1 % level. The positive effect of continuous R&D on the use of externally developed technologies may, for example, reflect that researching firms may incorporate new externally developed process innovations[32]. Furthermore, a positive impact is found for firms with a management team characterized by the presence of at least one technical degree, so that the importance of technical background for innovative activities is confirmed. A technical degree seems also to be needed to assess the usefulness of tech-

[32] The question in the survey was intended to also capture process innovation as it also asks for methods ("Verfahren").

nological innovations because we also find a positive effect on the probability of using new technologies developed by others with respect to being non-innovative. University degrees are particularly important for the self-development of technologies which is due to the fact that an academic background may enable the entrepreneurs to get in touch with cutting-edge technologies and to be able to refine them and develop a totally new product or process. Firms which are initially classified to have a medium risk display a lower probability of developing new technologies themselves with respect to being non-innovative. Interestingly, there is no significant effect of good rating with respect to bad rating.

Table 3.29.: Results for FIML multinomial logit accounting for endogeneity of VC financing

	Multinomial logit for innovativeness			Switching eq.
Model	**self**	**others**	**innovative**	
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
venture capital	10.983*** (2.414)	0.586 (2.167)	5.042** (2.261)	
continuous R&D	4.835*** (0.869)	0.978* (0.535)	1.963*** (0.695)	0.324** (0.141)
m_ graduate	1.356** (0.666)	-0.475 (0.320)	0.528 (0.533)	0.825*** (0.187)
m_ technical	1.298** (0.456)	0.710** (0.308)	1.118*** (0.431)	0.065 (0.128)
m_ majority	0.604 (0.567)	-0.354 (0.353)	0.352 (0.447)	-0.335** (0.155)
log(initial size)	0.157 (0.303)	0.077 (0.162)	-0.031 (0.230)	-0.093 (0.084)
good rating	-0.822 (0.671)	0.186 (0.518)	-0.412 (0.680)	0.394* (0.201)
medium rating	-1.514* (0.838)	-0.089 (0.527)	-1.100 (0.671)	0.070 (0.179)
log(distance)	0.170 (0.145)	-0.011 (0.075)	0.055 (0.116)	
East Germany	-0.599 (0.761)	0.619 (0.410)	0.298 (0.565)	0.115 (0.182)

(To be continued on next page)

	Multinomial logit for innovativeness			Switching eq.
Model	**self**	**others**	**innovative**	
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
number team				0.204*** (0.049)
m_ industry experience				0.203 (0.132)
pat_ before				1.125*** (0.258)
intermediate				0.467*** (0.120)
constant	-2.897* (1.566)	0.325 (1.106)	-0.190 (1.286)	-3.503*** (0.326)
industry dummies	included	included	included	included
foundation year dummies	included	included	included	included
ν	-4.994 (1.173)	-0.915 (1.154)	-2.815** (1.165)	
Log likelihood	-1,162.75			
LR(endogeneity) [a]	352.76***			
χ^2*(industries)* [b]	24.89*			
χ^2*(foundation year)* [c]	47.01***			
χ^2*(instruments)* [d]	58.85***			
BIC	-2976.03			
Number of observations	872			

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts coefficients of an endogenous switching multinomial logit model as proposed in Terza (2002) which corrects for the endogeneity of the binary variable VC financing in the multinomial logit by estimating simultaneously a multinomial logit model and a probit type VC equation by full-information maximum likelihood. The results for private VC are presented in Table B.10 on page 224 in the Appendix.

[a] LR(endogeneity) displays a LR-test of the two models showing that the endogeneity-corrected model is supposed to be the true one.

[b] χ^2(industries) displays a test of the joint significance of industry dummies.

[c] χ^2(foundation year) displays a test of the joint significance of foundation year dummies.

[d] χ^2(instruments) displays a test of the joint significance of instrumental variables in the VC equation. Clearly, the instruments are jointly significant.

3.5.6. Concluding remarks

This section investigates the impact of venture capital financing on firms' innovation activities by first looking at the relationship of patenting and VC financing. Second, the impact factors on firm's innovativeness are focused and VC financing is supposed to play a major role. The hypotheses tested in this chapter state that VC financing influences positively both patenting and innovativeness of a firm, particularly the probability of using self-developed new methods and technologies. For the investigation regarding patenting behavior, zero-inflated count data models are estimated and concerning the innovativeness issue a multinomial logit model is applied. Furthermore, we control for endogeneity of VC financing. We use FIML frameworks for both estimation methodologies and confirm the hypotheses that VC financing has a positive impact on patenting and on the probability of using self-developed and innovative combinations of tried and tested technologies with respect to use known combinations. Regarding the investment of private VCCs we confirm a positive effect on patenting if we control for endogeneity of VC financing and on the probability of using self-developed technologies.

Furthermore, we find, as expected, that continuous R&D activities are of utmost importance for innovation. Innovation experience is also an important input regarding firms' patenting as conjectured. For the innovativeness variable, we also confirm that technical education is indispensable for all categories. Academic background, and hence having the opportunity to come to know about the most recent scientific insights and research, is an important factor for self-development of methods and technologies.

4. Innovation and R&D activities and the business cycle

4.1. Motivation

Many corporate decisions are influenced by fluctuations in the business cycle. Particularly, firms' investment decisions may be subject to adjustments. A specific form of investment are capital inputs in R&D and innovation activities which can be seen as investments in firms' future profits and competitiveness. Those activities can also be interpreted as investment decisions with a long-term capital commitment so that adjustments cannot easily be made and fluctuations are assumed to be deviations from the mean (Hall (2002)). This chapter raises the question whether cyclical patterns in economic activities also influence firms' innovation and R&D behavior.

Generally, it is expected that there is no causal link between business cycle fluctuations and patterns in innovation activities since the duration of innovation projects usually exceeds the business cycle and most of the R&D investments are sunk. But it is suspected that there also is a short-term component in innovation activities that is linked to cyclical patterns in economic activity. Indeed, following the worldwide recession at the beginning of the 1990s, a decline in R&D expenditures took place in most OECD countries, whereas in the precedent periods they had increased more or less steadily, even during the downward trend in economic activity in the 1980s.

In the literature, the ways in which fluctuations in the business cycle and patterns in innovation activities are related are debated. Schumpeter (1939) states that innovations are not driven by the patterns of economic activity but that science and technology influence corporate and entrepreneurial activity and consequently the business cycle. This point of view is referred to as supply-push. According to Schmookler (1966), innovations depend crucially on the market demand (i.e. innovation activities tend to follow fluctuations in economic activity). This approach is called the demand-pull approach. Concerning this point of view, patterns in innovation activities can reflect the business cycle pro- and countercyclically. This chapter relies on Schmookler's approach and investigates whether fluctuations in the business cycle influence innovation and R&D behavior via market demand.

The effect of cyclical fluctuations on decisions to carry out innovation and R&D activities is tested empirically for German manufacturing between 1993 and 2000. We test for the adequate lag structure of the business cycle indicators since it is suspected that there is persistence in innovation activities (see e.g. Peters (2007)) and that R&D activities incorporate high adjustment costs which reduces the inclination to alter the process in the short-run (see e.g. Hall (2002)). The econometric model investigates whether innovation behavior, i.e. whether firms' innovation activities are persistent or discontinuous, depends on fluctuations in the business cycle. The dynamic process is reflected by transition probabilities which describe the change in the innovation state of a firm. These transition probabilities are modeled as first-order Markov chains. The model is estimated for all firms and for SMEs. Since it is suspected that SMEs are more vulnerable toward patterns in the business cycle.

The chapter starts with an overview of the literature that considers the link between innovation and economic activity. Section 4.2 describes the data. Section 4.5 summarizes the econometric model. The results are presented in Section 4.6.

4.2. Literature review

In this section, we first consider how innovation and R&D activities are related to each other and then we review the literature concerning the reasons why innovation and R&D activities are supposed not to alter much in the short-run. The ways in which R&D and innovation activities are linked is debated in the literature. First, the linear model of innovation represents the innovation process as a sequence of steps beginning with scientific research and ending with product development, market launch and marketing. In line with this concept, Ravenscraft and Scherer (1982) find that returns to R&D activities are bell-shaped with a maximum between four to six years. For some industries, like life science and chemistry, this linear concept fully applies (see Balconi et al. (2008)). Other approaches, however, challenge the linearity of the innovation process. For example, Kline and Rosenberg (1986) state that "a large part of the technological innovation that is carried out in industrial societies takes the form of very small changes, such as minor modifications in the design of a machine that will enable it to serve highly specific end users better, or that make it easier and therefore cheaper to manufacture...New science does sometimes make possible radical innovations. These occurrences are rare." (Kline, Rosenberg (1986), pp. 282). Kline and Rosenberg conceptualize these findings in the so-called chain-linked model which interprets the innovation process as a process of interactions between market opportunities and firms' knowledge and capabilities. Furthermore, it incorporates a continuous series of feedback between all parts of the process. In this respect, research is an adjunct to innovation (see OECD, Eurostat (1997)).

Theoretical literature provides some reasons why innovation behavior should follow a smooth path over time: The so-called "success breeds success" hypothesis provides one argument why innovation activities should persist. For example, successful innovations may increase market power permanently, and thus have a positive effect on the conditions for subsequent innovations. This argument goes back to Phillips (1971) who states that successfully innovating firms may dominate an industry permanently because of growing barriers to entry. Another argument can be trace back to Mansfield (1968) who argues that the success of firms' innovation activities discloses further technological opportunities, and hence increases the success probability of subsequent innovation (see also Stoneman (1983)). Thus, this strand of literature centers on locked-in advantages over competitors which is provided to the firms by innovations (Simons (1995)).

Furthermore, successful innovations contribute to the accumulation of knowledge and skills and to creativity (Nelson, Winter (1982), Malerba, Orsenigo (1993)). Hence, firms' absorptive capacities increase which escalate the accumulation of external knowledge in subsequent periods (Cohen, Levinthal (1990)).

Moreover, a substantial part of R&D investments is supposed to have a sunk cost character, and therefore they should follow a smooth path over time. This sunk cost character stems from the long time horizon and high initial investments, e.g. in machinery and highly qualified employees like scientists and engineers, and constitutes a barrier to entry and exit as regards R&D activities. Particularly, the skills and knowledge of the highly qualified employees are crucial for the innovation process. In this respect, as a major part of R&D expenditures is directed to the wages for those highly skilled workers (in Germany 62 % of total R&D expenditures, see Stifterverband (2004)), and R&D employees cannot easily be replaced, short-term adjustments of innovation activities are very costly (Hall (2002)), hence a long-term commitment towards innovation is expected (Sutton (1991)). Thus, R&D expenditures should evolve according to a smooth time path and should exhibit almost no dependencies with respect to short-term fluctuations in economic activity.

Empirical evidence on the persistence of innovation activities is often based on patenting behavior: Malerba and Orsenigo (1999), Geroski et al. (1997), Cefis and Orsenigo (2001) and Cefis (2003) find that only a small fraction of firms persistently innovate in terms of patenting but these firms patent in quite large numbers. Aside of the concern that patents are not good indicators of innovation activities (see e.g. Griliches (1990)), patents may not approximate persistence in innovation but persistence in innovative leadership (Duguet, Monjon (2004)).

Using innovation data, König et al. (1994) find evidence for persistence in process innovation, whereas Flaig and Stadler (1994) confirm persistencs for both product and process innovation. Other studies corroborating these findings are Duguet and Monjon (2004) and Rogers (2004). Peters (2007) find that innovation experience is an important driver for subsequent innovation activities. This finding is less prevalent in the service sectors. In contrast, Geroski et al. (1997) and Raymond et al. (2006) reject persistence in innovation behavior.

Despite the assumption that innovation activities follow a smooth path over time[33] some evidence can be found that a short-term component exists in innovation activities which is linked to the business cycle. Different explanations for the link between the dynamics in innovation and the business cycle are given by theoretical and empirical literature. The two most prominent examples are the so-called demand-pull and the supply(technology)-push approach.

Schumpeter can be counted among the advocates of the technology-push approach. He finds that a recession can be brought to an end by structural innovations that offer new opportunities for economic activity (Schumpeter (1934)). He also states that innovations are not driven by the patterns of economic activity but that science

[33] A reason why firms may stop innovating is, for example, that incumbent innovators may be reluctant to introduce new products or processes in order not to exhaust the returns on previous innovations (Schumpeter (1942)) or to reduce R&D investments with respect to challengers as predicted by patent race models (Reinganum (1983)).

and technology influence entrepreneurial activity and consequently the business cycle (Schumpeter (1939)). Kleinknecht (1987) approves Schumpeter's hypothesis by focusing on radical innovations and finds that they follow an uneven distribution over time. Kleinknecht (1990) reviews the theory of the Schumpeterian waves of innovations and models investments in capacity as a positive function of radical innovations, the number and impact of subsequent innovations, and the degree of diffusion. Another theory is proposed by Kleinknecht and Verspagen (1990). They state that launching innovations evokes multiplier and accelerator effects for market demand. Jovanovic and Lach (1997) analyze the relationship between innovation and economic activity empirically. They report that product innovations can explain fluctuations at lower frequencies but underestimate fluctuations at higher frequencies. This at least partly supports the supply-push approach.

Schmookler is considered one of the main proponents of the demand-pull approach. He states in his work 'Invention and Economic Growth' (1966) that innovation depends crucially on market demand[34]. Shleifer (1986) affirms that there are complementarities between aggregate demand and growth. He assigns this issue to aggregate demand externalities in the implementation of innovations.

The demand-pull approach allows for both pro- and countercyclical patterns in innovation behavior to respond to fluctuations in economic activity. One aspect of the countercyclical approach is the opportunity cost view. Aghion and Saint-Paul (1998) present a two-state Markov model. They assume that innovations tend to be countercyclical since opportunity costs decrease in recessions. But the overall effect depends on whether entry costs are fully recouped upon exit. Since the corresponding benefits are spread out over time. Consequently, it seems rational to invest in innovations during a recession[35].

Brockhoff and Pearson (1998) observe that R&D budgets are often cut as a consequence of a recession, which accounts for a procyclical reaction to changes in market demand. One possible explanation is that recessions may result in structural changes in firms' activity and consequently in the level and composition of their R&D budgets. Other

[34] Scherer (1982) tests Schmooklers's demand-pull hypothesis with a new and more comprehensive data set and challenges his results. Scherer states that the findings may be due to the fact that Schmookler concentrates on only few manufacturing industries. Expanding the set of industries leads to imperfect replications of the demand-pull result.

[35] Other opportunity cost approaches are provided by Davis and Haltiwanger (1990), Hall (1991), Gali and Hammour (1991) and Caballero and Hammour (1992).

arguments for procyclical patterns are provided by Himmelberg and Petersen (1994), Harhoff (1998), Bond et al. (2003), Mulkay et al. (2001), Bougheas et al. (2001) and Stiglitz (1993). They show that cash flow has a strong influence on R&D expenditures. Since cash flow is generated by firm activity the success of which also depends on the overall economic situation, it responds procyclically to fluctuations in market demand. Furthermore, markets have a limited capacity for absorbing new products (see Judd (1985) for a theoretical model). Therefore, the market launch of a new product is most probable when market conditions are favorable. Finally, if rival firms have a high potential to adapt and improve innovations, and consequently dissipate innovators' profits, innovating firms may time innovations such that the period of profit appropriation from innovative activities (which may be short) takes place during boom periods in order to be able to gain the maximum profits. Barlevy (2004) confirms that this conjecture holds for the market launch of new products as well as for the timing of the development of the innovation. This refers to as the strategic-timing effect.

The empirical investigations of the demand-pull approach are numerous. Saint-Paul (1993) applies a semi-structural vector-regressive (VAR) methodology. He states that there is little evidence of any pro- or countercyclical pattern of R&D particularly if the distinction between demand and supply shocks is made. Other studies find evidence supporting the demand-pull approach. Geroski and Walters (1995) employ count data on innovations and patents to investigate whether changes in demand cause fluctuations in innovations and patents. They conclude that changes in both innovation and patenting depend on demand and tend to be procyclical. Guellec and Ioannidis (1999) analyze the effect of multiple business cycle indicators on the level of R&D expenditures in several countries by means of aggregate sectoral data. They find that, in the case of Germany, heavy macroeconomic shocks (e.g. those caused by the reunification) had a detrimental effect on all forms of investment including R&D. Hall and Mairesse (1995) also find a procyclical pattern in R&D expenditures for French manufacturing. Smolny (2003) investigates the relationship between innovation behavior and business cycle indicators. He shows that in boom periods the level of innovation expenditures as well as the probability to innovate increase. Brouwer and Kleinknecht (1999) analyze firm-level R&D and find evidence of the important role of demand growth in varying R&D efforts. They state that this adds to the evidence that innovative output depends on demand. Procyclical effects of R&D can be found in Fatas (2000), Rafferty and Funk (2004). Aghion et al. (2004) confirm a procyclical response for countries with a low degree of financial development and a countercyclical behavior for countries with a high degree of financial development measured by the value of loans to the private sector relative to GDP. Giedeman et al. (2006) present mixed results for U.S. semiconductors and automobile industries investigating patenting activities. They detect procyclical behavior for large firms, and small firms in semiconductor industries, whereas small automobile firms reveal a countercyclical innovation behavior.

Le Bas (2000) estimates the effects on 'demand/R&D expenditures elasticities' with error correction models for seven OECD countries. Investment in R&D is described in terms of dynamic mechanisms which capture short- and long-term effects. He confirms a short-term effect of demand on R&D expenditures. The long-term effect turns out to be rather weak. Geroski and Machin (1993) show that innovating firms are less sensitive to cyclical shocks than non-innovating firms. This finding may be founded in a more flexible and adaptable behavior of innovators to new technological developments. They therefore conclude that "most firms, innovative or not, can prosper in a buoyant market, but only a few of the more innovative ones can continue to do so when the going gets tough."

Kleinknecht and Verspagen (1990) argue that demand-pull and technology-push effects might be complementary rather than mutually exclusive. This point of view is also supported by the neo-Schumpeterian literature. It is suggested that the relative weight of "demand-pull" and "supply-push" can vary with the industry stage and with the type of innovation. Technology-push is considered to be more important for innovative breakthroughs, while demand-pull seems to be more influential for subsequent innovations. In favor of this view is the result of Abernathy and Utterback (1975). They develop a life cycle model that relates the changing pattern of innovation to the increasing maturity of an industry. The conclusion is that the link of radical and subsequent innovations leads to diminishing returns on innovation towards the later stages of the life cycle.

Walsh (1984) analyzes the sensitivity of the chemical sector with respect to fluctuations in the business cycle and finds evidence for the neo-Schumpeterians approach. She states that "there is evidence to support both Schumpeter and Schmookler in the origins of the chemical sectors; in the secondary rapid growth phase there is evidence that market growth in the new products, resulting from the radical innovations, stimulated the swarming secondary innovations. The balance of 'supply' and 'demand' forces changed over the industry life cycles. In the mature phase of the industry sectors, with worldwide diffusion of innovation, the scale-up, the process innovations and more and more secondary product innovations in established product groups resulted from self-reinforcing upsurges in demand and secondary innovation. Finally, in all the sectors, various retardation factors have begun to slow down the growth rates and the rates of patenting, publication and technical advance."

Other explanations of the link between innovation and business cycle fluctuations is provided by the induced and the localized technological change approaches. Fluctuations in business cycles may change factor prices (Hicks (1932)) which in turn induce technological change, i.e. innovation. This induced technological change via the condition of the factor markets may explain the rate and the direction of innovation. An example is the CO_2 abatement policies which force firms to change the production technology if the existing one exceeds pre-defined thresholds in CO_2 emission (see Goulder, Schneider (1999)). A more recent approach is the so so-called localized technological change which combines bounded rationality (Simon (1982)), induced technological change, learning and irreversibility. The approach distinguishes between general technological change, i.e. a superior production function is defined, and contingent technological change which alters the output elasticities and hence the composition and ranking of production factors (Antonelli (2006)). Combining both the supply and the product market, this approach integrates demand pull and the Schumpeterian rivalry (Antonelli (2003, 1995)).

4.3. Stylized Facts and Hypotheses

Before deriving the hypotheses tested in this chapter, we present some stylized facts about cyclical patterns in economic and innovation activities in Germany for the period analyzed in this chapter. After the economic attenuation in the year 1987, the years 1988 to 1991 exhibited a boom period with growth rates between 3.5 and 5.5 %. The year 1991 was characterized by a maximum utilization of the economy's capacities and full employment which was mainly due to the German reunification in 1990, and the subsequent drastic increase in private demand. In the same year, the US experienced a recession which arrived in Germany with a one year time lag, and ended in the worst recession since World War II. The economic activity decreased by 1.1 %. The subsequent years until 1999 showed low growth rates of 0.8 % (in 1996) to 2.4 % (1994). The year 2000 was characterized by strong growth rates (3 %) but in the subsequent years growth rates returned to a low level, and Germany experienced a period of stagnation.

Innovation expenditures increased steadily between 1984 and 1991. This constant growth was not interrupted by the attenuation period in economic activities in the year 1987 nor was it speeded up by the boom period after the reunification in the years 1990/1991. Parallel to the recession in 1993/1994, innovation expenditures heavily decreased between 1992 and 1995. Since 1996 innovation expenditures increased stably. In contrast to R&D expenditures, innovation expenditures kept on augmenting during the weak growth period of the years 2001 and 2002.

Finally, the innovation participation is another important factor of the R&D and innovation behavior of firms. Beginning in the early 1980s up to the year 1998, the share of innovating firms with more than 200 employees increased more or less steadily which was only interrupted during the boom periods at the beginning of the 1990s and 1995/1996 displaying slightly decreasing participation rates. Since 1999 the share of innovators, however, decreases. As regards small firms, the share of innovating firms fluctuated between 42 and 48 %. In the 1980s, the quota increased until the boom phase of 1990/1991, in which the share, however, did not reach the maximum which was attained in the year 1988. A modest decrease followed the recession of the year 1993 whereas participation was quite stable between 50 and 54 % during the 1990s. The "boom" in 2000 did not translate in a higher innovation participation of small firms. In accordance with the economic downturn in the year 2001, the share of innovators within the group of small firms dropped, and reached the value of participation of the year 1986 (see Rammer et al. (2004)).

The hypotheses tested in this chapter rely on Schmookler's demand-pull approach. Therefore, we investigate whether there are cyclical patterns in innovation behavior caused by fluctuations in economic activities transmitted by market demand. This chapter tests whether the probability of a non-innovating firm to start to carry out innovation depends on the business cycle and if the decision of an innovating firm to continue to innovating depends on cyclical fluctuations. R&D and innovation activities may respond with different time lags to the business cycle: Innovation expenditures comprise two different types, a continuous and an investment part. Investments, e.g. in new machines, are usually supposed to respond strongly on fluctuations in the business cycle (see e.g. Tichy (1994) pp. 120) whereas continuous expenditures are mainly directed to the R&D process, particularly to the wages of R&D employees and may not easily be altered. Therefore, we assume that the lag structure of innovation and R&D activities may differ as concerns reactions to business cycle fluctuations.

Business cycle is generally defined as non-seasonal fluctuations in the level of economic activity. In the literature, several factors are discussed which are assumed to influence the innovation, and at the same time are considered to depend on the level of economic activities (see Guellec, Ioannidis (1999), Guellec, van Pottelsberghe (2001), Le Bas (2001), Geroski, Walters (1995), Geroski, Machin (1993)).

First, the business cycle has an impact on internal financing conditions. In times of high and growing demand, firms' profitability is usually good, and consequently, the possibilities to finance uncertain investments by cash-flow are favorable (see e.g. Himmelberg and Petersen (1994), Harhoff (1998), also see Section 3.2.1.2). The link between above-average profitability and boom periods is plausible. For example, if one thinks of short-term disequilibria on product markets: They lead to temporary price setting power of suppliers, i.e. to higher markups.

Second, business cycle fluctuations also change the supply and demand conditions on debt markets. A strong market growth increases the demand for debt, e.g. to finance expansion investments in times of high capacity utilization. As a matter of fact, the real interest rate rises and investments are more costly, including leveraged investment in innovation projects.

Third, patterns in economic activities may also have an impact on the prices for labor. For the financing of innovation activities, particularly, the wage for highly qualified personnel is important since almost two third of R&D expenditures consist of spendings for labor costs in Germany (see Rammer (2003)). Generally, the adjustment of real tariff wages react to business cycle fluctuations with a lag of one year.

Furthermore, changes in labor price also influence the demand for highly qualified personnel which may have an impact on innovation participation. Since the supply of highly qualified personnel is relatively constant over time and cannot be expanded in the short-run, a short-term demand shift for highly qualified may be a barrier to R&D projects. The lack of highly qualified labor may also shift firm activities in favor of production and commercialization and to the disadvantage of innovation projects.

Finally, investments in innovation depend on the technological success as well as on demand prospects for the totally new products. The current situation of supply and demand on the product market is the best predictor for future market development, i.e. growing markets are a sign of continued growth in the short-run and may stimulate uncertain investments, like R&D investments. Opposite to this scenario, shrinking demand may downturn the propensity to research.

To sum up, the impact of business cycle indicators on innovation activities are ambiguous. There may be pro- and counter-cyclical effects. We expect procyclical effects of market situation, capacity utilization and internal financing condition, and counter-cyclical effects of wages, lack in highly qualified labor and debt financing conditions.

Hypothesis 1: *The dynamics of innovation and R&D behavior is influenced by fluctuations in the business cycle.*

Hypothesis 1a: *The impact of different business cycle indicators may be ambiguous: Changes in market expectations, capacity utilization and internal financing conditions cause procyclical, whereas wages, debt financing conditions and lack of qualified labor trigger countercyclical reactions.*

Reactions to business cycle fluctuations may be different for small and for large firms. First, small firms may only have reduced possibilities to adjust R&D activities with respect to business cycle fluctuations, e.g. because of the minimum size of R&D projects. As a result, SMEs may adjust their R&D activities, e.g. by interrupting the projects. The assumed flexibility of SMEs regarding the re-orientation of resources between innovation and other activities like production would evoke the opposite effect.

Second, the financial structures of SMEs and large firms differ. In particular, SMEs are more dependent on debt financing, so that swayings in the real interest rates due to business cycle fluctuations may result in stronger adjustments by SMEs. Third, SMEs are assumed to be less active in internationalization than larger firms. This may result in a larger dependency on the domestic business cycle. At the same time, they are not as dependent on foreign business cycles, and international trends in R&D strategies are less relevant for them.

Finally, the management structure and legal form may differ. Large public companies may improve their gains by reducing the innovation costs whereas owner-managed small firms rely on a longer-term perspective. On the other hand, manager-led firms may be more risk-taking and research-oriented in order to attain above-average growth and consequently higher wages.

One final argument is that large firms with a diversified portfolio of business activities are in a better position to "cross-subsidize" their R&D activities by making use of the gains they generate in other fields. Thus, we conjecture that small firms are more affected by business cycle fluctuations with respect to their R&D projects (Rammer et al. (2004)).

Hypothesis 2: *Small firms' innovation and R&D activities are more vulnerable towards fluctuations in the business cycle.*

4.4. Data and descriptive considerations

The underlying data set consists of German firms in manufacturing industries surveyed in the MIP[36] during the years 1993 to 2000. Information on business cycle indicators is taken from the Business Climate Test of the Institute for Economic Research (Ifo) in Munich at the two-digit NACE level. The biennially published report of the German Monopolies Commission provides data regarding the market structure. The years in between are linearly interpolated. Indicators of market structure as used in Chapter 2 have been only included in the MIP in later years.

This study focuses on changes in the innovation and R&D participation of firms and estimates the model described in Section 4.5 separately for all firms and for SMEs defined as firms with less than 250 employees and sales less than 40 million Euro. This is in accordance with the definition of the European Commission (European Commission (2003)). The data set used for the econometric analysis consists of 6,081 observations on firms in the manufacturing sector, 60 % of which are SMEs.

The dependent variables of the econometric model are the innovation behavior and R&D activities in a specific year. But using the indicator of innovator provided by the MIP, we would run into the problem of measuring an extremely high persistence in innovation activities because this indicator does not reflect yearly innovation participation but the fact that the firm launched an innovation or abandoned an innovation project within

[36] For detailed description of the MIP see Appendix A.1.

the three years previous to the survey year. Thus, we need to account for overlapping time periods and double counting. Since information on innovation expenditures are available on a yearly basis we construct an innovation participation dummy which has unit value if a firm has positive innovation expenditures[37].

$$innovation_{it} = \begin{cases} 1 & \text{if innovation expenditures}_{it} > 0 \\ 0 & \text{if innovation expenditures}_{it} = 0 \text{ or innovator} = 0 \end{cases}$$

Innovation expenditures include expenditures for intra- and extramural R&D, innovation-related investments in machines and equipment, purchase of external knowledge (e.g. patents), training, market introduction, design etc. (see OECD, Eurostat (1997)). Hence, we define innovation activities by innovation inputs. Crépon et al. (1998) show that innovation inputs have a significant effect on innovation output, and hence the persistence patterns in the inputs should reflect the persistence in innovation outputs. R&D activities are defined accordingly[38].

$$R\&D_{it} = \begin{cases} 1 & \text{if R\&D expenditures}_{it} > 0 \\ 0 & \text{if R\&D expenditures}_{it} = 0 \text{ or innovator} = 0 \end{cases}$$

Relying in both definition on the innovator variable provided by the MIP is necessary because innovation as well as R&D expenditures are only asked if the firm stated that it was an innovator in the three previous years, i.e. we would underestimate the case in which the expenditures are zero. Only in the case when the MIP innovator indicator equals to zero we can be sure that this state also accounts for the current period.

According to Table 4.2, almost 60 % of the observations in the sample account for firms which are innovating. To describe a firm innovation behavior, the re-defined innovation dummy (see above) is transformed to capture the transition from an innovating to a non-innovating firm or vice versa between two periods, and thus, represent changes in firms' innovation behavior between two subsequent years. Assume one firm did not innovate in $t-1$, in period t it can either launch an innovation or not (decision$_{01}$ and decision$_{00}$). Another firm was innovating in $t-1$ and in period t it can either decide

[37] This procedure is in accordance with the one presented in Peters (2007)

[38] For the year 1997 (survey year 1998), no question on R&D was included in the MIP. Hence, we used the mean of the R&D expenditures of the previous and subsequent years, and assume that if this mean exceed 1 million € the firm was also performing R&D activities in the year 1997.

to keep on or to cease innovating (decision$_{11}$ and decision$_{10}$). Thus, four transition variables are constructed the definitions of which are as follows. Here is displayed the example for innovation, R&D is constructed accordingly:

$$decision_{00} = \begin{cases} 1 & \text{if innovation}_{i,t-1} = 0 \text{ and innovation}_{it} = 0 \\ 0 & \text{otherwise} \end{cases}$$

$$decision_{01} = \begin{cases} 1 & \text{if innovation}_{i,t-1} = 0 \text{ and innovation}_{it} = 1 \\ 0 & \text{otherwise} \end{cases}$$

$$decision_{10} = \begin{cases} 1 & \text{if innovation}_{i,t-1} = 1 \text{ and innovation}_{it} = 0 \\ 0 & \text{otherwise} \end{cases}$$

$$decision_{11} = \begin{cases} 1 & \text{if innovation}_{i,t-1} = 1 \text{ and innovation}_{it} = 1 \\ 0 & \text{otherwise} \end{cases}$$

where the first index of the decision variable refers to the innovation state in period *t-1* and the second to the state in period *t*. This variable definition leads to a Markov model with the aid of which transitions in behavior can be analyzed. The procedure is similarly applied to the definition of transition in the R&D status. Table 4.1 shows the distribution of the four transitions for all firms and for SMEs respectively.

As described in Section 4.3, we consider several factors which are directly linked to the patterns in economic activities and are supposed to influence innovation participation. The analyses are based on three indicators. They are taken from the Ifo Business Climate Survey and are measured as indices. The variable *lack of qualified labor* shows the variation in the labor market for qualified personnel with respect to the previous period. It exhibits a high value in boom periods since the demand for the scarce input of qualified labor is high during such stages. It is measured by the share of firms that agrees that the lack of qualified labor impedes their production. The variable *expected business development* represents the firms' perception of the expected business development. It is an indicator of how well businesses are expected to perform in the subsequent six months in terms of amelioration, downturn or leveling off. *Capacity* represents the demand conditions in the product market, i.e. a high market demand gives rise to a high level of production, which in turn leads to high capacity utilization ratio. Therefore, high capacity utilization is generally observed in periods of high economic activity. This variable is measured by the industry-average percentage that firms state as their capacity utilization.

Table 4.1.: Distribution of the four transitions for all firms and SMEs

	innovating in t	non-innovating in t	sum
Dynamics in innovation activities			
All firms			
innovating in t-1	2,923	855	3,778
non-innovating in t-1	609	1,694	2,303
Small- and medium-sized firms			
innovating in t-1	1,575	405	1,980
non-innovating in t-1	407	1,229	1,636
	researching in t	**non-researching in t**	**sum**
Dynamics in R&D activities			
All firms			
researching in t-1	2,507	273	2,231
non-researching in t-1	342	1,889	2,780
Small- and medium-sized firms			
researching in t-1	1,246	165	1,411
non-researching in t-1	229	1,473	1,702

In order to account for price changes in the factor markets – similarly to the theory of induced technological change (see Section 4.2) – we include *real* monthly *standard wages* to which the trade unions agreed and *real interest rates*[39]. Monthly standard wages – usually responding to fluctuations in the business cycle with a lag of one year

[39] Interest rates depict the average of the interest rates for credits between 100,000 and 500,000 € and between 500,000 and 2.5 million €. Industry differences become apparent by deflating with the corresponding 2-digit NACE producer price index. Information is taken from the time-series data of the Federal Statistical Office (Statistisches Bundesamt).

Table 4.2.: Descriptive statistics of R&D and innovation activities, transitions and business cycle indicators for all firms

Variable	Mean	Std.Dev.	Min	Max
innovation	0.581	0.493	0	1
R&D	0.569	0.495	0	1
$decision_{01}$ [a]	0.100	0.300	0	1
$decision_{00}$ [a]	0.279	0.448	0	1
$decision_{11}$ [a]	0.481	0.500	0	1
$decision_{10}$ [a]	0.141	0.348	0	1
Δ *exp. business develop.*	0.009	0.183	-0.743	0.747
Δ *capacity*	0.004	0.036	-0.116	0.193
Δ *lack of qualified labor*	0.002	0.038	-0.270	0.270
Δ *real standard wages*	0.240	0.192	-0.074	0.975
Δ *real interest rate*	-0.007	0.036	-0.113	0.090
Δ *pcm*	-0.065	0.245	-1.034	0.645
pcm_2	0.438	0.496	0	1
pcm_3	0.363	0.481	0	1
pcm_4	0.079	0.269	0	1
Δ *log(employees)*	-0.004	0.152	-0.652	0.613
size_2	0.160	0.367	0	1
size_3	0.200	0.400	0	1
size_4	0.262	0.440	0	1
Δ *diversification*	-0.005	0.153	-0.570	0.500
Herfindahl index(t-1)	0.040	0.050	0.003	0.376
market share(t-1)	0.004	0.012	0.000	0.140
human capital(t-1)	0.100	0.094	0.000	0.587
export intensity(t-1)	0.254	0.306	0.000	1.000
log(product life cycle(t-1))	2.147	0.825	-1.204	4.723
East Germany	0.328	0.469	0	1
number of observations		6,081		

Δ indicates that these variables are measured in first differences.

(t-1) indicates that these variables are measured lagged values.

[a] Transition for the innovation state. Transitions for the R&D state are not displayed.

Table 4.3.: Descriptive statistics of R&D and innovation activities, transitions and business cycle indicators for SMEs

Variable	Mean	Std.Dev.	Min	Max
innovation	0.548	0.497	0	1
R&D	0.473	0.499	0	1
$decision_{01}$ [a]	0.113	0.316	0	1
$decision_{00}$ [a]	0.340	0.444	0	1
$decision_{11}$ [a]	0.436	0.496	0	1
$decision_{10}$ [a]	0.112	0.315	0	1
Δ *exp. business develop.*	0.001	0.038	-0.590	0.747
Δ *capacity*	0.003	0.036	-0.116	0.193
Δ *lack of qualified labor*	0.002	0.038	-0.270	0.270
Δ *real standard wages*	0.235	0.182	-0.074	0.975
Δ *real interest rate*	-0.006	0.036	-0.113	0.090
Δ *pcm*	-0.070	0.251	-1.034	0.645
pcm_2	0.467	0.499	0	1
pcm_3	0.402	0.490	0	1
pcm_4	0.075	0.264	0	1
Δ *log(employees)*	0.001	0.160	-0.642	0.613
size_2	0.235	0.424	0	1
size_3	0.177	0.381	0	1
Δ *diversification*	-0.003	0.153	-0.569	0.500
Herfindahl index(t-1)	0.035	0.046	0.003	0.376
market share(t-1)	0.001	0.002	0.000	0.047
human capital(t-1)	0.101	0.099	0.000	0.581
export intensity(t-1)	0.179	0.274	0.000	1.000
log(product life cycle(t-1))	2.133	0.851	-1.204	4.605
East Germany	0.431	0.495	0	1
number of observations		3,616		

Δ indicates that these variables are measured in first differences.

(t-1) indicates that these variables are measured lagged values.

[a] Transition for the innovation state. Transitions for the R&D state are not displayed.

– and banks' debit interests at the two-digit NACE industry level are included in real prices. The development of prices in supply markets does not directly account for the business cycle. It is instead a reaction to fluctuations in economic activity seeking to level them out. Interest rates also account for the availability of external financing sources. They represent opportunity costs of innovation investment.

Table 4.2 shows the descriptive statistics for the variables included in the regressions of all firms, Table 4.3 of SMEs with less than 250 employees and 40 millions of sales, and Table 4.4 summarizes their definition. Besides economic activity, there are other factors that can influence innovation behavior which must be included in the regression to control for their potential influence on innovation participation. As an indicator of internal financing conditions the firms' price-cost margins (*pcm*)[40] are used. One indirect effect of a downturn in economic activity increases tension concerning internal financing conditions.

According to Schumpeter (1934, 1942), firm size and market structure are relevant for innovation activities. To reflect firm size, we rely on the number of *employees*. The effect of market power is ambiguous. Arrow (1962) shows that a monopolist's incentive to innovate is lower compared to inventors with no market share due to the expected loss of the monopolist's current profits if investing in R&D activities. Gilbert and Newbery (1982), instead, conclude that an incumbent monopolist tries to maintain its position through innovation and preemptive patenting. Czarnitzki and Kraft (2004) test empirically whether the incumbent or the challenger invests more in R&D. They state that the challenger invests more whereas the incumbent has no significantly higher R&D intensity. *Market share* and *Herfindahl index* are inserted as measures of the market structure. The Herfindahl is measured on a three-digit NACE level. Market share is defined as the share of firm sales with respect to three-digit NACE industry sales.

Furthermore, product diversification and firm-specific capabilities influence R&D activities, and it is assumed that product *diversification* and firm-specific capabilities favor R&D activities (see Gottschalk and Janz (2003) and Schasse (1998)). If a firm's product portfolio is highly diversified the dependence on business cycles in certain product

[40] The price-cost margin is defined as (sales - material costs - labor cost) / sales. The argumentation why this is an adequate representation of the price-cost margin is similar to the one presented in Section 2.1.3.1.

Table 4.4.: Variables description for estimation of the link between dynamics in R&D and innovation and business cycle

Variable name	Type	Description
Dependent variable		
$decision_{01}$	indicator	non-researching firm is starting to carry out R&D (similar for innovation)
$decision_{00}$	indicator	non-researching firm remains non-researching (similar for innovation)
$decision_{11}$	indicator	researching firm remains researching (similar for innovation)
$decision_{10}$	indicator	researching firm becomes non-researching (similar for innovation)
Explanatory variables		
exp. business develop. [ac]	index	firms' expectation about business development in the subsequent 6 months
capacity [ac]	index	industry capacity utilization in percent
lack of qualified labor [ac]	index	variations in market for qualified labor
real standard wages [a]	continuous	monthly standard wages in real prices
real interest rate [a]	continuous	banks' debit interest in real prices
pcm [a]	continuous	price-cost margin
Herfindahl [bd]	index	Herfindahl-Hirschman index of market concentration
market share [bd]	continuous	fraction of firm sales in the industry (3-digit)
employees [a]	continuous	number of employees
human capital [b]	continuous	proportion of highly qualified employees
export intensity [b]	continuous	share of sales generated by exports
product life cycle [b]	continuous	firm-average product life cycle
diversification [a]	continuous	share of sales generated by most important product
East Germany	indicator	firm location in East Germany
pcm_X	indicator	group of pcm clustered by lagged level
size_X	indicator	firm size clusters
industry dummies	indicator	8 industry dummies see Table C.1

[a] In the regression, the variables are included as lagged first differences.

[b] Variables included as lagged levels.

[c] Variables from the Ifo Business Climate Data Set merged at the 2-digit NACE level.

[d] Variables from the German Monopolies Commission provided at the 3-digit NACE level.

markets is smaller. To capture product diversification, we include the proportion of the respective most important product's sales to total sales.

Additionally, *export intensity* is included in the regression. Exporting is assumed to influence innovation activities. Firms trying to maintain exportation, and therefore strengthening their position in the international competition may be more inclined to keep on innovating, e.g. because the entry in foreign markets is associated to substantial sunk costs (Bernard and Wagner (2001)).

Endowment in *human capital* is also a crucial factor for innovation activities and can account for the firms' absorptive capacity (see Schmidt (2008)). This is described by a firm's proportion of highly educated employees to all employees, which is assumed to have a positive influence on innovation activities.

Moreover, firm's average *product life cycles*[41] are inserted as a measure of how large the incentive to innovate is. If the product life cycle is long the incentive to persistently innovate is low (Beise and Stahl (1998)). Industry dummies are also included in the equation to capture technological opportunities and industry-specific appropriateness (Schasse (1998)). The classification of the industry dummies can be found in Table C.1 on page 225 in the Appendix. Finally, an indicator of firms situated in *East Germany* is inserted because Eastern Germany still lags behind with respect to economic and innovative success.

Since our dependent variables show transitions from R&D and innovation states we conjecture that this dynamic depends on the dynamics in the variables described above. Therefore, we include those variables which are presumably time-varying as lagged differences. Those variables are the business cycle indicators, standard wages, interest rates, the price-cost margin, the proportion of sales generated by the most important product and the number of employees. Furthermore, we include dummies indicating the scale of size and price-cost margin because we conjecture that for those variables not only the differences account for transition but also the level[42]. The market structure,

[41] Missing values due to changing questionnaire designs of product life cycle, diversification, human capital and export intensity are filled by interpolating according to three-digit NACE level, year and size cluster (size clusters can be found in Table C.2 on 225 in the Appendix).

[42] We define four dummies for firm size: 5 to 50, 51 to 100, 101 to 250 and more than 250 employees. The dummy for the smallest firms is the reference category in estimations. Moreover, we include four dummies for the price-cost margin. One for negative price-cost margins (which is the base category), one for price-cost margins ranging from 0 to 0.25, one from 0.25 to 0.5 and one for price-cost margins larger than 0.5. All dummies reflect lagged values.

the degree of internationalization in terms of sales generated by export, product life cycle and the share of highly qualified do not vary much over time, hence those variables are inserted in lagged levels.

4.5. The econometric model

The dynamics in firms' innovation behavior is modeled by Markov chains which are a powerful instrument to model sequential decision making, and thus to study dynamic economic processes (Rust (1994), Van Nguyen et al. (2004)). Markov chains are defined as a sequence of random variables. They realize one of several possible states in a period, which depends crucially on transition probabilities and the initial state.

Markov chains can be used in the context of panel data with qualitative dependent variables (Gouriéroux (2000)). The qualitative variable y can take j=*0,...,J-1* different values and is observed t=*0,...,*T times. This variable constitutes a first-order Markov chain if y_t does not depend on previous values of y except through the intermediary effect of y_{t-1}.

$$Pr(y_t = j_t|y_{t-1} = j_{t-1}, ..., y_0 = j_0) = Pr(y_t = j_t|y_{t-1} = j_{t-1})$$

$$\forall t, j_t, j_{t-1}, ..., j_0. \tag{4.1}$$

This means that the chosen state in any period only depends on the state of the previous period. We estimate parametric versions of the Markov chain model. First, we present a model without heterogeneity (see 4.5.1) and then two models with different kind of unobserved heterogeneity (see 4.5.2).

4.5.1. Model without heterogeneity

The switch-over from state j to j' is modelled via the so-called transition probabilities $P_{ijj'}(t)$ for an individual i at time t, i.e. the probability that the status of firm i at time t (y_{it}) is j' given that the status in $t-1$ ($y_{i,t-1}$) has been j. These probabilities can be written as functions of exogenous variables. For the sake of simplicity, the transition probabilities are assumed to take logistic form, so that

$$P_{ijj'}(t) \equiv Pr(y_{it} = j'|y_{i,t-1} = j) = \frac{exp(x_{itjj'}\beta_{jj'})}{\sum\limits_{j'=1}^{J} exp(x_{itjj'}\beta_{jj'})}. \tag{4.2}$$

We only observe two states: carrying out R&D projects or not, i.e. $j = 0, 1$ and $j' = 0, 1$. For identification, we impose the assumption $\beta_{j0} = 0$. This results in

$$P_{ij0}(t) = \frac{1}{1 + exp(x_{it}\beta_{j1})} \tag{4.3}$$

$$and \tag{4.4}$$

$$P_{ij1}(t) = \frac{exp(x_{it}\beta_{j1})}{1 + exp(x_{it}\beta_{j1})},$$

with j=0,1. Let $n_{i,t-1,t}(jj') = 1$ if $y_{i,t-1} = j$ and $y_{it} = j'$, $n_{i,t-1,t}(jj')$ is 0 otherwise. The log-likelihood function conditional on the status in period $t - 1$ translates to

$$ln\mathcal{L} = \sum_{j=0}^{1}\sum_{j'=0}^{1} ln\mathcal{L}_{jj'}, \tag{4.5}$$

$$\text{with } ln\mathcal{L}_{jj'} = \sum_{i=1}^{N}\sum_{t=0}^{T} n_{i,t-1,t}(jj') lnP_{ijj'}(t).$$

Since $\sum_{j=0}^{1} ln\mathcal{L}_{jj'}$ only depends upon parameters β_{j1} (with $j = 0, 1$), the maximum likelihood estimator $\hat{\beta}_{j1}$ can be obtained by separately maximizing the elements of $\sum_{j=0}^{1} ln\mathcal{L}_{jj'}$ with $j = 0, 1$. Thus, the econometric model results in an estimation of two separate binary logit models. In this chapter, the first equation accounts for the decision of all non-researching firms whether to conduct R&D in the subsequent period or not, and the second for the decision of all researching firms whether to continue carrying out R&D activities. An application of Markov chains to firm performance can be found in Van Nguyen et al. (2004) and to internationalization strategies see Fryges (2004).

4.5.2. Model with heterogeneity

Van Nguyen et al. (2004) present a Markov chain model with a more general specification in that they allow for random effects. Two types of heterogeneity are considered: The first is linked to the "departure state" j (u_{ij}) and the second to the "transition" jj' ($u_{ijj'}$); both effects are also connected to the firm i. Other forms of heterogeneity – e.g. linked to the firm, the transition and the time period ($u_{ijj't}$) or only to the firm (u_i) – are not considered either for being not interesting or because of infeasibility. The corresponding likelihood conditional on the heterogeneity term is

$$\mathcal{L} = \prod_{j} \prod_{j'} \prod_{i} \prod_{t} \Big(P_{ijj'}(t) \Big)^{n_{i,t-1,t}(jj')}. \tag{4.6}$$

4.5.2.1. Random effects for firm and departure state

In the context of firm-departure state random effects, heterogeneity is represented by u_{ij}. These terms are assumed to be mutually independent, independent of the explanatory variables x_{it} and are standard normally distributed.

The transition probabilities keeping the identifying restriction $\beta_{j0} = 0$ can be expressed as follows

$$P_{ij0}(t) = \frac{1}{1 + exp(x_{it}\beta_{j1} + (\sigma_{j1} - \sigma_{j0})u_{ij})} \tag{4.7}$$

$$and \tag{4.8}$$

$$P_{ij1}(t) = \frac{exp(x_{it}\beta_{j1} + (\sigma_{j1} - \sigma_{j0})u_{ij})}{1 + exp(x_{it}\beta_{j1} + (\sigma_{j1} - \sigma_{j0})u_{ij})}. \tag{4.9}$$

For the model to be identified an additional restriction has to be imposed; we follow the approach of Van Nguyen et al. (2004) who choose to set $\sigma_{j0} = 0$.

Integration of (4.5.2.2) with respect to the heterogeneity distribution and taking the logarithms since u_{ij} are mutually independent and independent of x_{it} lead to the following log likelihood function

$$ln\mathcal{L}_j = \sum_i ln \int_{-\infty}^{\infty} \left(\prod_i \prod_t (P_{ij1}(t))^{n_{i,t-1,t}(j1)} \right) \phi(u_{ij}) du_{ij}.$$

To solve the integral we use a maximum simulated likelihood approach and replace the likelihood by the simulator

$$\frac{1}{H} \sum_{h=1}^{H} \prod_j \prod_t \left(P_{ij1}^h(t) \right)^{n_{i,t-1,t}(j1)}$$

where

$$P_{ij0}^h(t) = \frac{1}{1 + exp(x_{it}\beta_{j1} + \sigma_{j1}u_{ij}^h)} \ and$$

$$P_{ij1}^h(t) = \frac{exp(x_{it}\beta_{j1} + \sigma_{j1}u_{ij}^h)}{1 + exp(x_{it}\beta_{j1} + \sigma_{j1}u_{ij}^h)}.$$

For each u_{ij}, H pseudorandom draws of u_{ij}^h are generated.

4.5.2.2. Random effects for firm and transition

Firm-transition random effects are represented by $u_{ijj'}(t)$ which are assumed to be mutually independent and independent of x_{it} with a standard normal distribution. The respective transition probabilities maintaining the identifying restriction $\beta_{j0} = 0$ can be written as

$$P_{ij0}(t) = \frac{1}{1 + exp(x_{it}\beta_{j1} + \sigma_{j1}u_{ij1} - \sigma_{j0}u_{ij0})}$$

$$P_{ij1}(t) = \frac{exp(x_{it}\beta_{j1} + \sigma_{j1}u_{ij1} - \sigma_{j0}u_{ij0})}{1 + exp(x_{it}\beta_{j1} + \sigma_{j1}u_{ij1} - \sigma_{j0}u_{ij0})}.$$

In this case, σ_{j0} is identified. The simulated log likelihood function is

$$lnL_j = \sum_i ln\left(\frac{1}{H}\sum_{h=1}^{H}\prod_j\prod_t\left(P_{ij1}^h(t)\right)^{n_{i,t-1,t}(j1)}\right)$$

Both simulated log likelihood random effects estimators are programmed by ourselves using 30 simulation steps as proposed in Van Nguyen et al. (2004).

4.6. Empirical results

The aim of this chapter is to test empirically whether the dynamics in innovation and R&D activities depend on fluctuations in economic activity. This decision process is estimated by two separate equations, which are represented as first-order Markov chains (see Section 4.5.1). As a first step, we test which business cycle indicator reflects best the link between business cycle and innovation or R&D activities and which lag structure should be applied. The correlation structure between the indicators and between their differences reveals that high correlations prevail, therefore a selection is advisable. Furthermore, how the timing of the different variables (e.g. contradictory signs in capacity and the expected business development which reflect different timing issues) needs to be interpreted is not clear. Therefore, only one business cycle indicator and its lag structure is chosen by comparing the Bayesian Information Criteron (BIC) (see Table 4.5). According to the BICs, we choose the regressions including the differences in expected business development lagged by one year, except for the estimation of persistence in R&D activities where we include 6 lags.

As concerns the choice of the right model as discussed in Section 4.5, we perform LR tests. But since the models with random effects are non-nested, we further calculate

Table 4.5.: Specifying the appropriate business cycle indicator and lag structure using BIC

Lag structure [a]	lack qual. labor	exp. busi. dev.	capacity
non-innovating → innovating			
Lagged 1 period	-15,148.07	-15,150.65	-15,148.07
Lagged 2 periods	-15,140.35	-15,149.41	-15,141.89
Lagged 3 periods	-15,133.95	-15,142.88	-15,134.15
Lagged 4 periods	-15,127.61	-15,135.92	-15,127.09
Lagged 5 periods	-15,120.60	-15,128.68	-15,119.44
Lagged 6 periods	-15,112.94	-15,120.94	-15,112.87
Lagged 7 periods	-15,089.19	-15,117.90	-15,105.26
innovating → innovating			
Lagged 1 period	-27,537.91	-27,545.83	-27,537.25
Lagged 2 periods	-27,529.71	-27,538.22	-27,530.00
Lagged 3 periods	-27,521.51	-27,535.74	-27,523.15
Lagged 4 periods	-27,513.91	-27,527.63	-27,515.86
Lagged 5 periods	-27,507.66	-27,523.06	-27,522.10
Lagged 6 periods	-27,504.84	-27,527.73	-27,521.11
Lagged 7 periods	-27,500.77	-27,521.67	-27,520.34
non-researching → researching			
Lagged 1 period	-15,207.28	-15,213.23	-15,213.02
Lagged 2 periods	-15,201.21	-15,206.79	-15,206.05
Lagged 3 periods	-15,196.94	-15,201.43	-15,206.60
Lagged 4 periods	-15,189.80	-15,196.44	-15,204.13
Lagged 5 periods	-15,182.36	-15,199.46	-15,196.61
Lagged 6 periods	-15,176.16	-15,195.81	-15,189.77
Lagged 7 periods	-15,176.29	-15,188.11	-15,182.40
researching → researching			
Lagged 1 period	-20,271.68	-20,283.76	-20,272.38
Lagged 2 periods	-20,264.36	-20,278.47	-20,268.07
Lagged 3 periods	-20,259.34	-20,271.36	-20,260.83
Lagged 4 periods	-20,263.73	-20,264.91	-20,281.11
Lagged 5 periods	-20,255.84	-20,270.22	-20,281.00
Lagged 6 periods	-20,253.97	-20,297.89	-20,287.59
Lagged 7 periods	-20,262.71	-20,291.12	-20,281.51

This table depicts the BICs of regressions run in order to find out which is the appropriate business cycle representation and the corresponding lag structure. We also tested the lag structure of the variables *real standard wages* and *real interest rates*. The lag structure of those variables turns out to be not existent. Therefore, the BICs are not displayed. The BICs for small firms display largely the same figure (see Table C.3 on page 226 in the Appendix).

[a] All BICs reflect regressions including the lagged differences of the respective variable as well as the previous lags.

Table 4.6.: Model specification: BIC statistics and LR-tests

	Model for Transition	
	non → inno[a]	**inno → inno**[b]
BIC statistics[c]		
For all firms		
Logit	-15,150.65	-27,545.83
RE Transition[d]	-15,138.32	-27,529.44
RE Departure[e]	-15,143.81	-27,537.60
For all small- and medium-sized firms		
Logit	-10,160.47	-12,951.93
RE Transition[d]	-10,151.83	-12,937.29
RE Departure[e]	-10,155.87	-12,944.39
LR tests[f]		
For all firms		
Logit vs. RE Transition(2)	3.161	0.087
Logit vs. RE Departure(1)	0.905	0.003
For all small- and medium-sized firms		
Logit vs. RE Transition(2)	6.154	0.548
Logit vs. RE Departure(1)	2.795	0.055
	non → R&D[a]	**R&D → R&D**[b]
BIC statistics[c]		
For all firms		
Logit	-15,213.23	-20,297.89
RE Transition[d]	-15,200.81	-20,286.40
RE Departure[e]	-15,206.65	-20,294.05
For all small- and medium-sized firms		
Logit	-11,205.67	-9,147.71
RE Transition[d]	-11,194.04	-9,138.15
RE Departure[e]	-11,201.47	-9,141.64
LR tests[f]		
For all firms		
Logit vs. RE Transition(2)	2.997	4.371
Logit vs. RE Departure(1)	1.127	4.092
For all small- and medium-sized firms		
Logit vs. RE Transition(2)	3.241	4.942
Logit vs. RE Departure(1)	3.234	1.178

[a] This column shows the BIC statistics and LR tests for the firm transitions from non-researching to researching.
[b] This column shows the BIC statistics and LR tests for the firms' persistence to R&D activities.
[c] The model with the most negative BIC statistic is the one to choose. This clearly points at the Logit model in all four models.
[d] This row represents the model with random effects incorporating heterogeneity for firm and transition.
[e] This row represents the model with random effects incorporating heterogeneity for firm and departure state.
[f] The LR tests are χ^2 distributed with degrees of freedom represented in brackets.

the BICs to choose the most suitable model. Both criteria are displayed in Table 4.6. The BICs suggest that the models without heterogeneity are the ones that fit best in the context of cyclical effects in firm's innovation activities. The results of the models with heterogeneity can be found in the Appendix pp. 227.

Table 4.7 presents the marginal effects of logit regressions pertaining to both the decision of non-innovating firms to start to innovate and of innovating firms to persist in innovating for all firms in the sample and for SMEs. Results for non-researching firms to conduct R&D in the subsequent period and the effects which cause a researching firm to keep on carrying out research projects are displayed in Table 4.8.

First looking at the results for innovation activities (Table 4.7). A negative sign of expected business development is confirmed for the persistence of innovation activities. This suggests that innovating firms respond countercyclically to fluctuations in the business cycle. The effect for SMEs is significantly higher, i.e. their reaction to business cycle fluctuations is stronger. The countercyclical reaction can be explained with opportunity costs. As stated by Aghion and Saint-Paul (1998), opportunity costs of innovation decrease in recessions, and hence investments in innovation become more attractive for the firms. Furthermore, we run the regressions with splitted business development expectations in order to find out which effect drives the countercyclical behavior. One regressor accounts for positive differences, hence the influence of boom periods, and a second for negative ones, thus the impact of recessions. For innovation, we find that only the effect in downturn periods is the substantial impact factor of the countercyclical behavior. Hence, in downturn periods firms tend to persist in innovating.

As regards the control variables, we find a positive effect of increasing standard wages which may be explained by the fact that, if the input factor labor is getting more expensive, firms tend to start to innovate in order to develop a technology which enables them to reduce labor in the production process. The factor price of labor also has a negative effect on the probability to persist in innovating. Since innovation activities are knowledge- and hence labor-intensive an increase in the factor price of labor may provoke firms to cease innovating. The negative effect of interest rates show that, as external financing gets more expensive, firms tend to postpone their innovation activities. With respect to the internal financing conditions captured by the price-cost margin we find a negative impact of increasing price-cost margins which may reflect

Table 4.7.: Regression results for the dynamics of innovation activities

	non-innovating → innovating		innovating → innovating	
	all firms	**SMEs**	**all firms**	**SMEs**
	Marg.Eff. (Std.Err.)	**Marg.Eff. (Std.Err.)**	**Marg.Eff. (Std.Err.)**	**Marg.Eff. (Std.Err.)**
Δ *exp. business develop.*	-0.084	-0.080	-0.120***	-0.153***
	(0.052)	(0.062)	(0.041)	(0.053)
Δ *real standard wage*	0.086*	0.157***	-0.061*	-0.104**
	(0.047)	(0.058)	(0.036)	(0.051)
Δ *real interest rate*	-0.765***	-0.785**	-0.128	0.155
	(0.253)	(0.310)	(0.183)	(0.236)
Δ *pcm*	-0.094**	-0.065	0.003	0.019
	(0.037)	(0.042)	(0.027)	(0.033)
pcm_2	0.235***	0.054	0.349***	0.035
	(0.040)	(0.050)	(0.019)	(0.036)
pcm_3	0.278***	0.085	0.329***	0.051
	(0.045)	(0.053)	(0.017)	(0.036)
pcm_4	0.337***	0.081	0.191***	0.017
	(0.064)	(0.075)	(0.010)	(0.043)
Δ *log(employees)*	0.180***	0.118*	-0.073	0.031
	(0.063)	(0.070)	(0.045)	(0.055)
size_2	0.123***	0.128***	0.080***	0.089***
	(0.034)	(0.034)	(0.017)	(0.020)
size_3	0.143***	0.150***	0.097***	0.081***
	(0.034)	(0.041)	(0.016)	(0.021)
size_4	0.217***		0.145***	
	(0.040)		(0.018)	
Δ *diversification*	0.000	0.003	-0.094**	-0.104*
	(0.064)	(0.075)	(0.042)	(0.054)
Herfindahl(t-1)	-0.077	-0.268	0.301*	0.458*
	(0.236)	(0.293)	(0.164)	(0.241)
market share(t-1)	0.014	0.010	0.005	0.098
	(0.012)	(0.053)	(0.006)	(0.092)
human capital(t-1)	0.192	0.356**	0.265***	0.282**
	(0.127)	(0.140)	(0.091)	(0.114)
export intensity(t-1)	0.061*	0.074**	-0.118***	-0.057*
	(0.031)	(0.036)	(0.024)	(0.034)
log(product life cycle(t-1))	-0.017	-0.023*	-0.017*	-0.034***
	(0.011)	(0.013)	(0.010)	(0.013)
East Germany	-0.002	0.011	0.040**	0.024
	(0.023)	(0.025)	(0.017)	(0.020)
industry dummies	*included*	*included*	*included*	*included*
log likelihood	-1,238.91	-880.47	-1,679.60	-944.10
χ^2(all) [a]	146.24***	68.03***	502.61***	94.52***
χ^2(industries) [b]	9.93	3.48	35.36***	16.38**
McFadden's R^2	0.069	0.041	0.169	0.059
McFadden's adjusted R^2	0.049	0.013	0.156	0.034
Cragg-Uhler's R^2	0.111	0.066	0.251	0.091
BIC	-15,150.65	-10,160.47	-27,545.83	-12,951.93
number of observations	2,303	1,636	3,778	1,980

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the marginal effects of logit models which are calculated at the sample means. Marginal effects of dummy variables are interpreted as discrete change from 0 to 1. Standard errors are clustered by firm and transformed using the delta method.

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(industries) displays a test on the joint significance of industry dummies.

a business cycle effect, as margins are supposed to increase in boom periods, firms would then tend to postpone their innovation activities. This effect is insignificant for the persistence of innovation activities. The amount of available internal financing has a positive effect for the starting decision as well as for persistence. For SME, no significant effect of the price-cost margins are found. This may hint at the point that they may have relatively high price-cost margins (as also suggested by the descriptives) but the amount of available financial sources may be smaller compared to larger firms. Since innovation projects are often characterized by a minimum size this may explain the insignificant impact of the price-cost margin for SMEs.

As firms grow they tend to start to innovate and persist in innovating. Positive effects are also found for the size effects. If the most important product tends to generate a higher share of sales, i.e. firms get less diversified, firms have a higher probability to leave the innovation state. Thinking about firms which usually incrementally improve their products (in line with Kline and Rosenberg (1986)), this finding would suggest that firms concentrating on fewer products have a lower probability to persistently innovate, e.g. because they have marginally improved the products, and then want to benefit from sales generation.

Furthermore, we find that in more concentrated markets the firms tend to more persistently innovate. This finding may be due to two effect: First, similar to the argument of Gilbert and Newbery (1982) that established large firms try to reinforce their market position. Or second, in line with the findings of Czarnitzki and Kraft (2004) that "smaller" entrant firms would invest more in order to catch up with the incumbents. Moreover, we confirm the importance of human capital for the innovation process as a high share of highly qualified employees has a positive impact on persistence and on starting to innovate for SMEs. Internationally active firms tend to start to innovate which is in accordance with the prediction. The result on persistence is quite puzzling. This effect may be interpreted as such: Firms which are generating quite a low share of sales by exports have trespassed the barrier to entry in the international markets. As their exports are quite low they need to persistently innovate in order to reinforce their international competitiveness. Finally, if the product life cycle is shorter the probability to start to innovate is higher for SMEs and the probability to persist in innovating for all firms is higher as well which corresponds to the expected effect.

Table 4.8.: Regression Results for the dependency of R&D decision on business cycle fluctuation

	non-researching → researching		researching → researching	
	all firms	**SMEs**	**all firms**	**SMEs**
	Marg.Eff. (Std.Err.)	**Marg.Eff. (Std.Err.)**	**Marg.Eff. (Std.Err.)**	**Marg.Eff. (Std.Err.)**
Δ *exp. business develop.*	-0.107*** (0.039)	-0.124*** (0.042)	-0.092*** (0.025)	-0.101*** (0.036)
$\Delta 2$ *exp. business develop.*			0.017 (0.021)	0.049 (0.033)
$\Delta 3$ *exp. business develop.*			0.004 (0.023)	-0.013 (0.035)
$\Delta 4$ *exp. business develop.*			0.016 (0.025)	0.037 (0.041)
$\Delta 5$ *exp. business develop.*			-0.016 (0.024)	-0.032 (0.035)
$\Delta 6$ *exp. business develop.*			-0.125*** (0.021)	-0.176*** (0.036)
Δ *real standard wage*	0.095*** (0.036)	0.105*** (0.041)	-0.049* (0.027)	-0.036 (0.044)
Δ *real interest rate*	-0.647*** (0.185)	-0.597*** (0.211)	0.125 (0.122)	0.208 (0.192)
Δ *pcm*	-0.007 (0.030)	0.011 (0.033)	0.030** (0.015)	0.043* (0.023)
pcm_2	0.084** (0.033)	0.033 (0.035)	0.077*** (0.015)	0.049** (0.024)
pcm_3	0.076** (0.037)	0.029 (0.037)	0.065*** (0.013)	0.038 (0.024)
pcm_4	0.098* (0.057)	-0.002 (0.044)	0.046*** (0.008)	0.023 (0.023)
Δ *log(employees)*	0.003 (0.049)	-0.015 (0.049)	0.036 (0.028)	0.080* (0.043)
size_2	0.080*** (0.029)	0.081*** (0.027)	0.019** (0.009)	0.025* (0.014)
size_3	0.134*** (0.032)	0.114*** (0.036)	0.034*** (0.009)	0.028* (0.015)
size_4	0.185*** (0.041)		0.060*** (0.011)	

(To be continued on next page)

	non-researching → researching		researching → researching	
	all firms	**SMEs**	**all firms**	**SMEs**
	Marg.Eff. (Std.Err.)	**Marg.Eff. (Std.Err.)**	**Marg.Eff. (Std.Err.)**	**Marg.Eff. (Std.Err.)**
Δ *diversification*	-0.036	-0.009	-0.075***	-0.069*
	(0.047)	(0.048)	(0.025)	(0.037)
Herfindahl(t-1)	-0.107	-0.028	0.151	0.339*
	(0.180)	(0.196)	(0.098)	(0.175)
market share(t-1)	0.012	0.016	0.013**	0.141*
	(0.011)	(0.046)	(0.005)	(0.074)
human capital(t-1)	0.211**	0.241***	0.076	0.051
	(0.088)	(0.088)	(0.053)	(0.079)
export intensity(t-1)	0.046*	0.059**	0.042**	0.021
	(0.025)	(0.025)	(0.019)	(0.029)
log(product life cycle(t-1))	0.000	-0.006	-0.004	-0.000
	(0.008)	(0.009)	(0.006)	(0.008)
East Germany	0.023	0.036*	0.043***	0.058***
	(0.019)	(0.019)	(0.008)	(0.015)
industry dummies	*included*	*included*	*included*	*included*
log likelihood	-893.89	-635.23	-751.12	-433.69
χ^2(all) [a]	105.15***	70.76***	245.96***	121.81***
χ^2(industries) [b]	19.05**	13.33	58.65***	27.57***
χ^2(lag) [c]			71.11***	48.37***
McFadden's R^2	0.065	0.055	0.159	0.148
McFadden's adjusted R^2	0.037	0.018	0.124	0.089
Cragg-Uhler's R^2	0.094	0.078	0.204	0.197
BIC	-15,213.23	-11,205.67	-20,297.89	-9,147.71
number of observations	2,231	1,702	2,780	1,411

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the marginal effects of logit models which are calculated at the sample means. Marginal effects of dummy variables are interpreted as discrete change from 0 to 1. Standard errors are clustered by firm and transformed using the delta method.
[a] χ^2(all) displays a test of the joint significance of all variables.
[b] χ^2(industries) displays a test on the joint significance of industry dummies.
[c] χ^2(lag) displays a test on the joint significance of all lagged differences of the expected business development.

As regards R&D activities, we find that continuously researching takes into account the business cycle development of a longer period as the sixth lag is significant. The long-term coefficient of continuous R&D activities, i.e. accounting for all lagged effects is -3.477 (-3.471 for SMEs). The long-term coefficient is significant at the 1 % level. The long-term marginal effect is -0.286 (-0.232 for SMEs). Hence, firms tend to adjust their decision to start to carry out and to continuously perform R&D activities countercyclically. Also for R&D activities we run the regressions with splitted business cycle variable and find that countercyclical behavior of non-researching firms is driven by the effect in boom periods. Hence, firms tend to postpone their R&D activities if the overall economic situation is favorable. As regards continuing R&D activities, the long-term countercyclical effect is only dominant in downward periods hinting at persistent R&D activities in recessions. Both effects are also found for SMEs. The difference of the effects is not significantly higher for SMEs. The continuous performance of R&D activities may be a rational decision since opportunity costs decrease in recessions. Another criteria may be the timing of a new product's market launch. Since the R&D process takes some time until the outcome may be ready for market launch it would be advisable to do research during recession periods and to launch the product in times when markets are more favorable. The different figure as regards starting innovation or R&D activities may account for the long-term commitment of R&D activities. Since adjustments are not easily made, firms may be reluctant to enter the research state if economic activity is favorable. Innovation activities if represented in terms of inputs to the innovation process may reflect more incremental innovations.

Furthermore, we confirm most effects as for the innovation estimation. As price-cost margin increases firms tend to continuously research which is in line with the findings that R&D activities are constraint by internal financial conditions. Firm growth in terms of employees has, as opposed to the innovation activities, no effect on the dynamics of R&D activities. A higher market share increases the probability of continuously researching which may be due to enforcing the own market position. The signs of exports are now as predicted. Firms carry out R&D activities if they generate a higher share of sales by exports. Finally, the highly significant positive effect of the East Germany dummy on the probability to persist in researching for SMEs may reflect the fact that specific public funding schemes exist for East German firms to which Western German firms have no access. This subsidization is committed to continued R&D activities so that these firms may be more inclined to keep on researching (Czarnitzki (2001), Czarnitzki, Licht (2004)).

4.7. Concluding remarks

This chapter aims at showing whether there is a relation between fluctuations in economic activity and firms' R&D and innovation behavior. Schmookler (1966)'s approach pointing out that innovations depend crucially on market demand is the baseline of this chapter. In order to investigate firm's R&D and innovation behavior, the dynamics in R&D and innovation activities is modeled via first-order Markov chains. They are described by four binary variables: They indicate firms starting to innovate, firms remaining non-innovating, firms that keep on innovating and innovating firms ceasing to carrying out innovation activities (similarly for R&D). The specification of the regression function includes expected business development as an indicator for the business cycle as well as firm characteristics and the market structure.

The estimations reveal that R&D and innovation activities respond countercyclically to fluctuations in the business cycle: firms decide to persistently innovate if the expected business development decreases, hence during recessions. For R&D activities, we find short-term countercyclical effects for the decision to start to innovate, particularly in boom periods firms tend to postpone their entry in the R&D state, and long-term effects for the decision to persistently innovate. In recession periods, the opportunity costs of innovation and R&D decrease, hence firms keep on carrying out R&D and innovation activities. If firms are not performing R&D activities they would renounce on starting to research if the overall economic situation is favorable. In boom periods, firms have the possibility to profit from the generally good situation and generate some profits. The slightly different patterns in innovation and R&D activities may be due to higher adjustment costs of the R&D process. The adjustment costs may be higher for R&D activities than for innovation because we look at innovation inputs in terms of expenditures, and innovation activities may also reflect incremental innovation. We find evidence that SMEs respond to cyclical fluctuations in the same manner than all firms. For the probability of persistently innovate and to start research activities the reactions of SMEs are supposed to be more intense since the marginal effects are significantly higher.

5. Summary & Conclusions

5.1. Summary

This thesis presents empirical evidence on three different aspects of industrial organization: Entrepreneurship, innovation and competition. In Chapter 2, we investigate whether firms are disciplined by threat of entry as conjectured by the literature (see Baumol et al. (1982)). Furthermore, we test the predictions of a model on the optimal number of competitors in a market depending on fixed and marginal costs. Both questions are addressed using a survey-based data set in which firms were asked to assess their competitive situation with respect to the number and size of competitors, price competition and threat of market position due to potential market entry. Particularly, the information on threat of entry is unique since usually econometricians lack data on this issue and approximate it with actual market entry.

Under the assumption that entry occurs until profits are dissipated, threat of entry is supposed to discipline incumbent firms not to exert their price setting power, and thus, to accept reductions in their profitability in order to impede entry. The results support the theoretical assumption that threat of entry has a disciplinary effect on incumbent firms with respect to the price setting behavior since we find that threat of entry has a negative impact on firms' return on sales. This negative effect is interpreted as a consequence of entry threat on incumbents' price setting behavior in that they approach competitive prices.

Furthermore, we present a model on the number of competitors in a market. We relate the number to fixed costs, which should represent at least partly sunk costs. We also find that it depends on marginal costs. The model predicts that both have a negative effect on the number of competitors. This theoretical result is confirmed by the empirical investigation. Furthermore, we test whether threat of entry causes the firms to reduce their profits to such an extent that entry is unattractive. This test is carried out by the estimation of the impact of threat of entry on the number of firms. Since there is no significant effect we confirm that prices are set in such a way that profits are low enough to render market entry unattractive, i.e. incumbents behave competitively.

In our test on threat of entry, we also control for the competitive situation of the firms by using survey-based information instead of relying on standard concentration indices to represent the market structure. This approach takes into account the results of Section 2.2 where we address the usefulness of industry-based concentration indices in investigations regarding the relation of market structure and firm behavior which is proxied ba the possibility of generating profits. This approach relies on the linear SCP paradigm despite of the fact that it is "old-fashioned" in recent industrial organization studies as it is not able to account for feedback effects. Nonetheless, we use this framework to show whether concentration indices are useful measures in reflecting market structure. We use industry-based concentration indices like the Herfindahl and the C3 and C6 concentration indices and survey-based data on the number and size of competitors, price competition and buyer power as indicators of the competitive situation of firms. We find that survey-data clearly outperforms industry-based concentration indices. We relate this to the definition of the relevant market which can be better reflected by the perception of firms as gathered in survey data than relying on a relatively broad industry-based definition.

Improvements of the analyses may be achieved by using panel data set. Before-after comparisons would help to solve or attenuate the diverse endogeneity and causality issues, which can hardly be totally avoided in the case of cross-sectional data. Unfortunately, this rich set of competition variables we used, was only provided in the MIP survey of the year 2005.

Chapter 3 deals with a specific form of entrepreneurial finance, venture capital, which is assumed to play a crucial role for highly risky firms in high-technology industry. Since VC investors are often said to be active investors also having the right to influence the structure of the firms' top management we investigate this by looking at VCCs' impact regarding changes in the initial executive team. As opposed to previous literature, we look at changes in the executive teams instead of the dismissal of the CEO. Therefore, we define different kinds of changes that may occur in the top management: replacement of at least one member by another executive, enlargement and reduction. The definition of the categories is such that the categories are not overlapping so we estimate the probabilities of the respective changes by using a multinomial logit framework. We find that VCCs have no impact on the probability of executive replacement or other types of changes if we control for the high selectivity of the VC investment process. Hence, we discover that the observed positive correlation between VC financing and changes in the executive team are a mere selection effect. If this selection is taken into account no differences to non-VC-backed firms is detected as concerns replacements, and VC-backed firms have a lower probability to experience enlargement of the top management. Particularly the result of replacement contradicts the findings of other studies which usually do not account for the endogeneity of VC financing. Furthermore, we investigate the time until the first change happens by using discrete hazard models accounting for unobserved heterogeneity, and find that indeed VC-backed firms experience replacements in the executive teams earlier than their non-VC backed counterparts. But we suspect that this effect would vanish if we could account for the selectivity of VC financing as in the multinomial logit estimations. The robustness check for private VCCs shows that the effects are basically the same for return oriented VCCs.

Since one of the most prominent reasons for changes in the executive team is bad firm performance, it should improve as a result of changes in the top management. Therefore, we test whether firm performance enhances if changes occur to the top management. Since information on return on equity, return on assets, return on sales or price-cost margin is lacking we use growth in terms of employment and labor productivity to test for changes in performance. For growth, we are not able to perform the strong test whether changes in the top management improve performance by looking at the differences in growth before and after the change occurred. Therefore, we look at the effects of short-term growth. For labor productivity, we try to find the determinants of the change in labor productivity between the first and the last observation. We find that return-oriented private VCCs have a positive impact. The effects of VC- and non-VC-induced changes also improve performance in terms of labor productivity. For the growth equation, we confirm negative effects of VC interventions in the top management. This may be due to the fact that our "time-series" is quite short and effects of changes would emerge if we take into account a longer gap between the changes and the measurement of performance in terms of labor productivity and firm growth. This may be subject to future research as well as to solve the endogeneity problems present in these analyses. In a nutshell, although the impact of active investors on changes is revealed to be a selection effect, their involvement in the firm influences firm performance.

In Section 3.5, we investigate the impact of VC financing on innovation activities in young high-tech firms. Innovation is reflected by the number of patents and by a variable called innovativeness. The latter is a categorical variable with four different characteristics and displays the specificities of the top-selling product. This top-selling product may be characterized by the use of new methods and technologies which have been self-developed by the firm or externally developed, or by the usage of tried and tested methods and technologies either in an innovative or a known combination. The last category corresponds to being non-innovative. The variable is intended to reflect both product and process innovations.

In order to test the hypotheses of the impact of VC financing on patenting, we use zero-inflated count data models, and regarding the innovativeness, we employ a multinomial logit framework. Furthermore, we test if the active involvement of the VC investor in the firm has a positive impact by running the regressions including the indicator "investment by a private VC company". Private VCCs are assumed to have a higher level of expertise and experience so that their involvement is assumed to be more valuable for the firms. Another robustness check looks at the number of patents per year in order to account for productivity effect in terms of patents. We find that (private) VC investors have a positive impact on the average number of patent applications per year, and hence on firms' patenting productivity.

Since VC financing includes a severe due diligence process the positive effects of VC financing on patenting and innovativeness may only report a selection issue. In order to correct for the endogeneity of the VC dummy, we estimate FIML versions of the count and multinomial logit model in which we simultaneously estimate the probability to receive VC financing. Even if we correct for endogeneity the impact is still positive and significant. A limitation regarding the endogeneity-corrected count model is that we are not able to account for excess zeros which should be included if we recall the results of the zero-inflated count models which show that zero-inflation needs to be accounted for. We find that (private) VC financing has a positive impact on both firms patenting behavior[43] and the probability of using new self-developed methods and technologies compared to using known combinations of technologies.

[43] If we control for excess zeros, the positive effect of private VC financing vanishes.

One main limitation of the analyses so far is the lack of panel data. With panel data we could account for individual heterogeneity and could better identify timing effects. Firms evolve particularly within the first years after their emergence, when structural changes are most present. Furthermore, their needs change substantially during this period and it would be very interesting to pursue their development and how for example financing, strategies regarding market entry etc. develop over time and on which factors they would depend. In a couple of years, this would be feasible. In the year 2008, the so-called KfW-ZEW Foundation Panel was kicked off which aims at tracing a sample of entrepreneurs in high-tech and non-high-tech sectors. Furthermore, information regarding the amount of VC investment and the share a VC investor holds and changes to it would be very valuable and could be better proxies for the active VC involvement. Finally, the effect of syndicated VC investments, as pointed out in Section 3.2.2, could also be interesting to investigate.

In Chapter 4, the impact of fluctuations in the business cycle on the dynamics of firms' innovation and R&D decision is investigated. These dynamics are modeled as first-order Markov chains of the transition from one period to the subsequent one. Two transitions are modeled and estimated: the decision to start to innovate(research) and the decision to persist in innovating(researching). Information from the Business Climate Survey of the Ifo Institute is used to reflect factors that are directly linked to patterns in economic activities and are also supposed to influence innovation(R&D) decision. Specification tests revealed that business cycle fluctuations are most adequately reflected by expected business development. Moreover, for the estimation of continuing R&D activities lags of six years seem to be appropriate so that we use the respective lag structure of the business cycle indicator. Furthermore, first differences of the real tariff salaries, real banking interest rate and internal financing condition, represented by the price-cost margin, and firm size are included because these variables also react to fluctuations in the business cycle and are assumed to influence the innovation decision. Variables regarding market structure, export intensity, product life cycle, diversification and human capital are not varying much over time and are hence included in lagged levels.

The results show that indeed countercyclical patterns exist in firms' innovation and R&D decision. Non-researching firms postpone their activities if the business development is expected to increase. The decision to start to innovate does not depend on fluctuations in the business cycle. These differing effects may be due to the higher adjustment costs in R&D activities. Firms which already perform innovation or R&D activities tend to persist in innovating and researching if future business development is supposed to experience a downturn which also accounts for countercyclical reactions to fluctuations in the business cycle. As regards SMEs we find the same countercyclical effects. In downturn periods, their innovation activities and in boom periods their R&D activities respond more intensely to cyclical fluctuations.

Other interesting topics in this respect are the determination if business cycle factors influencing product and process innovations. Furthermore, the influence of business cycle on the impediments of innovation activities may also be part of future research, particularly the impediments of financial constraints. One hypothesis is that financial constraints worsen in recessions and firms with good innovation projects may postpone or even abolish their innovation projects because the financial constraints weigh heavy.

5.2. Conclusion

As described in the Introduction, innovation policy at the European level aims at reaching the 3% target of the R&D intensity with respect to GDP. Guellec and Sachwald (2008) rank this target to focus on the symptom but not on the problem itself and its structural causes. They identify two main fields of action to attain this goal: First, the improvement of the excellence of academic research as concerns quality, flexibility and openness to society. Second, the encouragement of new firm creation in emerging sectors, particularly in technology and knowledge-intensive sectors, and thus sustaining the innovation performance in the EU by promoting innovation projects by young and innovative firms which do not have the same financial means and access to contracts as established firms. A reason, why the emergence of new businesses in technology-oriented sectors is supposed to contribute substantially to innovativeness, is the assumption that new companies are created to exploit a specific technological or commercial opportunity which oftentimes has been neglected by large companies, e.g. because they do not realize its market potential. In this sense, radical breakthroughs are supposed to be mainly developed by new companies, and established firms are better at incremental innovation which are intended to strengthen their market position.

A first step towards creating conditions which are favorable to the emergence of technology-oriented firm foundation at the EU level has been made by opening out into the discussion about a “Small Business Act” for Europe carried on by the Commission. Some plans of activity relate to the access to funding, the fostering of innovation in SMEs and profiting of the growth of markets. For example, regarding the financing problems of SMEs, the Commission will inspect the possibilities of establishing cross-border private investments in order to strengthen the European venture capital markets. Concerning the innovation potential, the Commission claims that SMEs need to be integrated in the community of researching firms and to expand the cooperations between universities and SMEs (Commission of the European Communities (2008)).

As traced in the introduction, the emergence of new firms also has other effects besides the expected one on innovativeness: It is assumed to have a substantial impact on competition. In Section 2, we could confirm the theoretical hypothesis that the mere threat of entry already induces less opportunistic behavior by incumbents. Even in markets in which the number of competitors is bounded because of the existence of entry barriers, threat of entry aligns the incumbents’ behavior to be more competitive. Hence, also from a competition point of view, entrepreneurial activity, as one pillar of market entry, is important. But not only barriers to entry may prevent market entry of young firms, financial constraints are one of the most prominent impediments to the creation and the development of new firms. Particularly, for new innovative companies, the provision of external finance is limited. Thus, a vivid market for entrepreneurial finance may also affect incumbents’ market behavior indirectly in that it facilitates entry, and consequently also increases the entry threat by newly created firms. This suggests that entrepreneurial activity – and indirectly also entrepreneurial finance – is crucial not only for the economy’s sustainability, innovativeness and growth but also for the inducement of competitive behavior of incumbent firms.

Another aspect of entrepreneurial activity on incumbents, which is raised by Guellec and Sachwald (2008), is the conjecture that incumbents may be forced to invest more in innovation because of increasing competitive pressures caused by the (possibility of) emergence of new entrants. This aspect has not been considered in this thesis but the investigation of the perceived threat of entry and incumbents’ innovation activities deserves further research. Innovation by incumbents should be encouraged when they are confronted with threat of technologically advanced entry, particularly when the sectors are close to the technological frontier. Aghion et al. (2006) call this the escape-entry effect. Furthermore, incumbents being much behind the technology frontier may be discouraged to perform innovation because of increased entry threat. The argument is similar to Aghion et al. (2005) who find an inverted-U-shaped relation between competition and innovation. Aghion et al. (2006) are only able to rely on actual entry to test their model. Another concept that also favors a positive effect of threat of entry is the so-called pre-emptive patenting hypothesis by Gilbert and Newbery (1982) in which the incumbent tries to strengthen his market position, and thus impede market entry by innovation (see also Sutton (1991)). With our original measure of threat of entry, we could investigate its impact on incumbents' innovation and patenting activities.

In the light of the recent financial crises, the accentuation of innovation policy may need to change because the financial crisis initiating in the U.S. already one year ago has reached the real economy. The result of the newest report of the German expert advisory board concerning the economic situation (Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung) is that the recession which was suspected to arise for over a year will materialize soon (see Sachverständigenrat (2008)). This has also an impact on the inclination of conducting innovation activities and firm start-ups, i.e. the recession will not only affect existing firms but also the creation of new firms.

Regarding the impact of the prospective recession on the dynamics of R&D and innovation activities, the findings of Chapter 4 show that in recessions innovation and R&D activities will be more probably persistent. Furthermore, R&D activities seem to be postponed in periods of economic downturn if the firm is not yet carrying out R&D. But in contrast, expected business development has no impact on starting innovation activities. This result may also be of political importance: Our results suggest that innovation policy, e.g. the "innovation offensive" and the so-called "high-tech strategy"[44] of the German Federal Government, need not to be adjusted during recessions as firms tend to respond countercyclically to business cycle fluctuations. However, the dimension of the recently started downturn, which already showed quite strong turbulences on financial markets, is not yet clear. If the downturn will be as strong as it is forecasted and also last quite a long time maybe the patterns in R&D and innovation activities will change. The data set includes downturn periods but not with the extent that is predicted for the recent recession.

In addition, the recession may particularly affect the emergence of new firms. As broadly discussed in Section 3.2.1, young technology-oriented firms often lack funds

[44] The aim of this strategy is the increase of R&D and innovation participation of SMEs.

to finance their research projects. In recessions, their funding gap is more difficult to bridge because the supply of financial sources for this segment will also suffer from the downturn, and young high-tech firms may not be able to absorb this, at least partly, by relying on internal sources of finance as large established firms may be able to do.

Chapter 3 focuses on a specific financial instrument which is often perceived to be tailored to the needs and characteristics of young innovative firms: Venture capital. As shown in Section 3.5, VC investors could be a driver of entrepreneurial innovation. Therefore, VC is – as assumed by many policy makers also in the European Commission – an important factor in supporting innovation activities in young SMEs.

However, in times of an economic recession, two effects may work at reducing the total amount of VC investments available. First, VC companies may have difficulties in raising funds. A large part of funds is usually provided by banks and assurance companies which are most of all affected by the financial crisis and its consequences. But also other investors of VC funds, like large corporations, may be more reluctant to invest because they may also (expect to) be affected by the crisis. Second, VC companies themselves may also be more cautious regarding their investment opportunities and may invest less funds than in boom periods because they are aware that start-up growth and performance are much more difficult to achieve in downturn periods. Particularly, if firms are innovative and still have to struggle for an adequate market place, it is difficult in times when the general situation is unfavorable. Therefore, they may be more selective towards financing young technology-oriented firms.

Although the financial crisis already casted its shadows one year ago, the German VC market still defies a downturn. According to Fleischhauer, Hoyer & Partner Private Equity Consultants[45], the number of investments increased in the third quarter of this year with respect to the second quarter. Hence, German VCCs seem to be unperturbed as regards the financial crisis. But if the suspected drop in fund raising comes true, a decrease in the number and amount of investments will occur.

Finally, a claim of Guellec and Sachwald (2008) is that funding should also include public funds, as besides the structural change in innovation policy, resources are crucial factors concerning the functioning of entrepreneurship. In Germany, a new instrument aimed at seed funding has been established in 2005, the so-called High-tech founders fund (High-Tech Gründerfonds). Six technology-oriented large incumbents – BASF,

[45] Refer to www.fhpw.de.

Bosch, Daimler, Deutsche Telekom, Siemens and Zeiss – invest together with the Federal Ministry of Economics and Technology and the Kreditanstalt für Wiederaufbau (KfW) in innovative firms which are not older than one year. This fund is aimed at seed financing up to 500,000 € per deal. In total, about 272 million € have been raised. Currently, over 100 firms are funded. This instrument also tries to bridge some of the gaps that may hinder a good start-up performance (like management skills, aid in setting up a business plan, subsequent funding etc.) in that this association cooperates with different partners like research institutions which have start-up initiative to promote own spin offs (e.g. the Fraunhofer-Gesellschaft Venture Gruppe), coaches and other investors. Consequently, this instrument may alleviate the impacts of the financial crisis for innovative entrepreneurs: First, it is an instrument in a sector that has been neglected a long time, particularly after the collapse of the high-tech markets, which is seed financing. Second, because of the close cooperation with experts in academia and management, receiving funds may certify a certain quality of the firm. Thus, the companies are able to reduce the substantial information asymmetries, and may be able to attract scarce financial resources by other types of investors, like VC companies.

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A. Appendix: Competition and Profitability

A.1. The Mannheim Innovation Panel

The Mannheim Innovation Panel (MIP) is an annual survey of all firms in Germany with at least five employees, active in manufacturing, mining, knowledge-intensive service sectors and selected other services. This survey is conducted since 1993 by the Centre for European Economic Research (ZEW) in Mannheim on behalf of the Federal Ministry of Education and Research (BMBF). The aim is to collect information on the innovation behavior of German firms.

The innovation survey is designed to be a panel, i.e. each year the same sample is surveyed. Due to attrition, this data set is expanded every two years by a random sample of newly founded firms. Biennially, the survey is a so-called "long survey" (odd years) including additional questions regarding innovation, e.g. the financing of innovation projects, and the remaining years it consists of a "short survey" asking for the central innovation indicators, like product and process innovation, innovation expenditures.

The underlying definitions and measurement concepts correspond to the recommendations of the OECD and Eurostat fixed in the "Oslo Manual". Furthermore, the MIP is regularly (currently, every second year) part of the Community Innovation Survey (CIS) coordinated by Eurostat.

The sample is stratified according to industry, firm size clusters and region (East and West Germany). The response rate is usually about 20 %. In order to avoid distortions in the answering behavior of the firms, a non-response analysis is done with every new wave for a fraction of the non-responding firms.

Table A.1.: Classification of industry dummies for Chapter 2

Dummy	Description	NACE
industry dummy 1	Food, beverage and tobacco	15, 16
industry dummy 2	Textile, clothes and leather goods	17, 18, 19
industry dummy 3	Wood, paper, publishing, printing, furniture, jewellery, musical and sport instruments, toys and others	20, 21, 22, 36, 37
industry dummy 4	Fuels, chemicals, rubber and plastic products	23, 24, 25
industry dummy 5	Non-metallic mineral products	26
industry dummy 6	Basic metals and fabricated metals	27, 28
industry dummy 7	Machinery and equipment	29
industry dummy 8	Office, data processing, electrical machinery and components, communication equipment	30, 31, 32
industry dummy 9	Medical, optical instruments and watches	33
industry dummy 10[1]	Motor vehicles and components and other transports	34, 35

[1] Industry dummy 10 is the base category in estimations.

B. Appendix: Venture capital in German high-tech entrepreneurship

B.1. High-tech industries

Table B.1.: List of high-tech industries used in the telephone survey

Manufacturing sectors	
NACE Code	**Industry**
2233	Reproduction of computer media
2330	Processing of nuclear fuel
2411	Manufacture of industrial gases
2412	Manufacture of dyes and pigments
2413/2414	Manufacture of other inorganic and organic basic chemicals
2417	Manufacture of synthetic rubber in primary forms
2420	Manufacture of pesticides and other agro-chemical products
2430	Manufacture of paints, varnishes and similar coatings, printing ink and mastics
2441	Manufacture of basic pharmaceutical products
2442	Manufacture of pharmaceutical preparations
2461	Manufacture of explosives
2462	Manufacture of glues and gelatines
2463	Manufacture of essential oils
2464	Manufacture of photographic chemical material
2466	Manufacture of other chemical products

(continued on next page)

NACE Code	**Industry**
2911	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
2912	Manufacture of pumps and compressors
2913	Manufacture of taps and valves
2914	Manufacture of other general purpose machinery
2931	Manufacture of agricultural tractors
2932	Manufacture of other agricultural and forestry machinery
2940	Manufacture of machine tools
2952	Manufacture of machinery for mining, quarrying and construction
2953	Manufacture of machinery for food, beverage and tobacco processing
2954	Manufacture of machinery for textile, apparel and leather production
2955	Manufacture of machinery for paper and paperboard production
2956	Manufacture of other special purpose machinery
2960	Manufacture of weapons and ammunition
3001	Manufacture of office machinery
3002	Manufacture of computers and other information processing equipment
3110	Manufacture of electric motors, generators and transformers
3140	Manufacture of accumulators, primary cells and primary batteries
3150	Manufacture of lighting equipment and electric lamps
3162	Manufacture of other electrical equipment
3210	Manufacture of electronic valves and tubes and other electronic components
3220	Manufacture of television and radio transmitters and apparatus for line telephony and line telegraphy
3230	Manufacture of television and radio receivers, sound or video recording or reproducing apparatus and associated goods

(continued on next page)

NACE Code	Industry
3310	Manufacture of medical and surgical equipment and orthopaedic appliances
3320	Manufacture of instruments and appliances for measuring, checking, testing, navigating and other purposes, except industrial process control equipment
3330	Manufacture of industrial process control equipment
3340	Manufacture of optical instruments and photographic equipment
3410	Manufacture of motor vehicles
3430	Manufacture of parts and accessories for motor vehicles and their engines
3520	Manufacture of railway and tramway locomotives and rolling stock
3530	Manufacture of aircraft and spacecraft
Technology-oriented service sectors	
642	Telecommunications
72	Computer and related activities
731	Research and experimental development on natural sciences and engineering
742	Architectural and engineering activities and related technical consultancy
743	Technical testing and analysis

B.2. Conception of the ZEW Hightech Founders Survey 2006

The ZEW Hightech Founders Survey was conducted in the year 2006. The underlying population is the ZEW Foundation Panel.

B.2.1. ZEW Foundation Panel

Since its foundation the ZEW cooperates with Creditreform, the largest credit rating agency in Germany. It is used constantly for the sake of building up several firm panels (see Stahl (1991), Harhoff, Steil (1997) and Almus et al. (2000) for more details on panel data sets based on Creditrefrom data). The data is provided semiannually containing updated and newly gathered data entries.

Creditreform is decentrally organized. Currently, 134 independent offices collect information in a standardized manner in order to provide information on firms' creditworthiness. Investigation focuses on the legally independent firm which may consist of several establishments.

Information provided to the ZEW are firm name and address, legal form, industry affiliation, number of employees, sales, foundation date, information on insolvency proceedings, date of last investigation, information on owners and managers.

The information sources which Creditreform uses are manifold: Public register like the commercial register, daily newspaper, business reports, published balance sheet information and personal interviews. The most important triggers for an entry of newly founded firms are the commercial register and requests of firms or persons who want to check the creditworthiness before establishing a business relation.

B.2.2. Identification of the basic population underlying the telephone interviews

On the basis of the ZEW Foundation Panel, the population for the telephone survey has been defined. The two conditions which firms needed to fulfil are their industry affiliation – we concentrate on high-tech industries, see Table B.1 for reference – and the year of firm foundation.

We further exclude firms lacking information regarding the ZIP code, since besides the name of the firm it is mandatory to identify a firm if any reinvestigation would be necessary. Only one percent of the basic population lacked the ZIP Code. Furthermore, all firms are excluded for which Creditreform has entered a closing comment. After this cleaning procedure we end up with 73,000 firms.

Table B.2.: Distribution of stratification criteria in the basic population

	high-tech 1	high-tech 2	hardware	software	tech. serv	total
1996 to 2000	839	2,743	2,489	10,971	20.554	37,596
2001 to 2005	763	3,088	2,250	10,767	18,868	35,736
total	1,602	5,831	4,739	21,738	39,422	73,332

Source: ZEW Foundation Panel

The distribution of the basic population according to sectors and cohorts is given in Table B.2. From this basic population, a sample of 8,000 firms has been drawn randomly for the distribution in the stratified sample). 1,085 of which have been interviewed on the telephone. The resulting sample of interviewed firms is stratified. The first stratification criteria is the foundation date which have been clustered into two periods, the boom- and post-boom-phase of high-tech industries in Germany. The second stratification criteria is based on the industries.

Table B.3.: Distribution of industries and cohorts in the stratified sample and respective probabilities of draw

	high-tech 1	high-tech 2	hardware	software	tech. serv	total
1996 to 2000	680	920	680	840	880	4,000
2001 to 2005	680	920	680	840	880	4,000
total	1,360	1,840	1,360	1,680	1,760	8,000

Stratified sample underlying the telephone survey for industry clusters and cohorts including the drawing probabilities, i.e. the probabilities of firms in the population being part of this industry-cohort combination of being “drawn” into the sample.

For high-tech manufacturing three clusters have been identified. First, the so-called "Spitzentechnik" (high-tech1) with an industry R&D intensity of above 8 %; second, the so-called "Hochwertige Technik" (high-tech2) with an industry R&D intensity between 3.5 % and 8 %. Finally, from both high-tech clusters in manufacturing the hardware sector has been separated. Regarding service sectors, we consider technology-intensive services from which we take apart the software industries. The distribution of the stratified sample is depicted in Table B.3. After a three-weeks survey period we gathered 1,085 completed interviews. It was necessary to contact 6,315 firms so that we have a response rate of 17 %.

B.3. Question for innovativeness

This is a translation of the question in the survey regarding innovativeness of the firms. The question has been asked in the context of the most important product or service with respect to sales.

In the following we want to know more about the characteristics of your product/your service. I read some statements. Please tell me whether these statements apply to your product/your service.

1	Is your product/service characterized by the input of new methods and technologies, which have been developed by your firm?
2	Is your product/service characterized by the input of new methods and technologies, which have been developed by other firms?
3	Is your product/service characterized as an innovative combination of tried and tested methods and technologies?
4	Is your product/service characterized as an established combination of tried and tested methods and technologies?

Table B.4.: Cloglog models for time until change

	Replacement	Enlargement	Reduction
	Haz.Rat. (Std.Err.)	**Haz.Rat. (Std.Err.)**	**Haz.Rat. (Std.Err.)**
venture capital	2.615***	1.658	0.787
	(0.614)	(0.552)	(0.413)
log(number team)	2.230***	1.557**	3.443***
	(0.378)	(0.317)	(0.797)
log(initial size)	1.141***	1.040	1.047
	(0.054)	(0.060)	(0.070)
m_graduate	1.289	1.139	1.611
	(0.299)	(0.288)	(0.496)
m_technical	0.933	0.788	1.120
	(0.170)	(0.165)	(0.279)
m_indexp	1.855***	1.514	1.121
	(0.444)	(0.390)	(0.316)
m_above55	2.559***	0.853	1.060
	(0.535)	(0.322)	(0.430)
m_majority	0.651*	0.824	0.556*
	(0.152)	(0.203)	(0.189)
good rating	0.694	1.598	0.956
	(0.187)	(0.661)	(0.417)
medium rating	0.756	2.128**	1.137
	(0.180)	(0.805)	(0.444)
cont. R&D	1.000	1.828***	0.564**
	(0.183)	(0.381)	(0.154)
East Germany	0.965	0.826	0.765
	(0.209)	(0.236)	(0.260)
log(t)	0.632***	0.600***	1.010
	(0.083)	(0.092)	(0.180)
constant	0.018***	0.010***	0.008***
	(0.008)	(0.005)	(0.005)
industry dummies	*included*	*included*	*included*
log likelihood	-540.51	-440.38	-335.82
χ^2 *(all)* [a]	138.30***	61.37***	61.58***
χ^2 *(industries)* [b]	3.63	7.33	3.43
McFadden's R^2	0.113	0.065	0.084
McFadden's adjusted R^2	0.084	0.027	0.035
Cragg-Uhler's R^2	0.129	0.072	0.091
BIC	-33,594.01	-33,430.48	-33,387.94
number of observations	4,177	4,138	4,111

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the hazard ratios of discrete cloglog duration models. The dependent variables are *time until replacement*, *time until enlargement* and *time until reduction.*

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(industries) displays a χ^2-test on the joint significance of industry dummies.

Table B.5.: Cloglog models for time until change (private VC funding)

	Replacement	Enlargement	Reduction
	Haz.Rat. (Std.Err.)	**Haz.Rat. (Std.Err.)**	**Haz.Rat. (Std.Err.)**
private	3.317*** (0.847)	1.612 (0.653)	0.535 (0.389)
log(number team)	2.188*** (0.370)	1.561** (0.318)	3.470*** (0.804)
log(initial size)	1.163*** (0.056)	1.045 (0.060)	1.046 (0.069)
m_ graduate	1.274 (0.295)	1.144 (0.289)	1.618 (0.498)
m_ technical	0.938 (0.170)	0.794 (0.166)	1.126 (0.281)
m_ indexp	1.877*** (0.449)	1.512 (0.389)	1.127 (0.318)
m_ above55	2.630*** (0.555)	0.858 (0.324)	1.056 (0.428)
m_ majority	0.653* (0.153)	0.826 (0.204)	0.552* (0.187)
good rating	0.741 (0.198)	1.647 (0.683)	0.948 (0.413)
medium rating	0.765 (0.183)	2.141** (0.811)	1.147 (0.448)
cont. R&D	1.022 (0.186)	1.859*** (0.386)	0.567** (0.154)
East Germany	1.014 (0.219)	0.859 (0.244)	0.759 (0.258)
log(t)	0.635*** (0.084)	0.600*** (0.091)	1.008 (0.179)
constant	0.018*** (0.007)	0.010*** (0.005)	0.008*** (0.005)
industry dummies	*included*	*included*	*included*
log likelihood	-538.86	-440.79	-335.48
χ^2 *(all)* [a]	141.59***	60.54***	62.25***
χ^2 *(industries)* [b]	4.36	7.44	3.41
McFadden's R^2	0.116	0.064	0.085
McFadden's adjusted R^2	0.087	0.026	0.036
Cragg-Uhler's R^2	0.132	0.071	0.092
BIC	-33,597.30	-33,429.65	-33,388.62
number of observations	4,177	4,138	4,111

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the hazard ratios of cloglog duration models. The dependent variables are *time until replacement*, *time until enlargement* and *time until reduction*.

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(industries) displays a χ^2-test on the joint significance of industry dummies.

Table B.6.: Results for risk-competing discrete hazard model

	Replacement	Enlargement	Reduction
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
venture capital	1.064*** (0.253)	0.547 (0.344)	-0.220 (0.533)
log(number team)	0.859*** (0.176)	0.458** (0.207)	1.257*** (0.235)
log(initial size)	0.140*** (0.050)	0.041 (0.059)	0.050 (0.067)
m_graduate	0.257 (0.236)	0.138 (0.255)	0.470 (0.311)
m_technical	-0.071 (0.188)	-0.235 (0.214)	0.111 (0.254)
m_indexp	0.645*** (0.245)	0.413 (0.261)	0.111 (0.286)
m_above55	1.024*** (0.224)	-0.150 (0.384)	0.094 (0.414)
m_majority	-0.427* (0.239)	-0.190 (0.250)	-0.586* (0.343)
good rating	-0.410 (0.281)	0.441 (0.418)	-0.055 (0.441)
medium rating	-0.306 (0.249)	0.748* (0.383)	0.143 (0.396)
cont. R&D	-0.018 (0.189)	0.606*** (0.212)	-0.589** (0.277)
East Germany	-0.055 (0.227)	-0.215 (0.291)	-0.280 (0.345)
log(t)	-0.481*** (0.136)	-0.525*** (0.156)	0.005 (0.181)
constant	-4.029*** (0.430)	-4.561*** (0.533)	-4.774*** (0.589)
industry dummies		*included*	
log likelihood		-1,326.83	
χ^2*(all)* [a]		256.00***	
χ^2*(industries)* [b]		14.32	
McFadden's R^2		0.088	
McFadden's adjusted R^2		0.051	
Cragg-Uhler's R^2		0.117	
BIC		-33,337.92	
number of observations		4,350	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts the coefficients of a competing-risk duration model. As opposed to the other duration models displayed in this section, in this model all equations are estimated simultaneously.

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(industries) displays a χ^2-test on the joint significance of industry dummies.

Table B.7.: Results for risk-competing discrete hazard model (private VC)

	Replacement	Enlargement	Reduction
	Coeff. (Std.Err.)	Coeff. (Std.Err.)	Coeff. (Std.Err.)
private vc	1.292***	0.512	-0.590
	(0.280)	(0.420)	(0.735)
log(number team)	0.842***	0.461**	1.262***
	(0.176)	(0.207)	(0.235)
log(initial size)	0.156***	0.044	0.049
	(0.050)	(0.059)	(0.067)
m_ graduate	0.247	0.143	0.474
	(0.235)	(0.255)	(0.310)
m_ technical	-0.065	-0.229	0.118
	(0.188)	(0.214)	(0.254)
m_ indexp	0.663***	0.413	0.112
	(0.245)	(0.261)	(0.286)
m_ above55	1.039***	-0.154	0.088
	(0.225)	(0.384)	(0.413)
m_ majority	-0.416*	-0.187	-0.593*
	(0.240)	(0.251)	(0.343)
good rating	-0.343	0.468	-0.055
	(0.279)	(0.418)	(0.441)
medium rating	-0.297	0.755**	0.154
	(0.249)	(0.383)	(0.396)
cont. R&D	0.005	0.623***	-0.584**
	(0.189)	(0.211)	(0.276)
East Germany	-0.007	-0.173	-0.284
	(0.227)	(0.289)	(0.344)
log(t)	-0.464***	-0.523***	0.002
	(0.136)	(0.156)	(0.182)
constant	-4.056***	-4.574***	-4.785***
	(0.430)	(0.533)	(0.590)
industry dummies		*included*	
log likelihood		-1,325.64	
χ^2 *(all)* [a]		258.38	
χ^2 *(industries)* [b]		14.97	
McFadden's R^2		0.089	
McFadden's adjusted R^2		0.052	
Cragg-Uhler's R^2		0.118	
BIC		-33,340.30	
number of observations		4,350	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts the hazard ratios of a competing-risk duration model. As opposed to the other duration models displayed in this section, in this model all equations are estimated simultaneously.

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(industries) displays a χ^2-test on the joint significance of industry dummies.

Table B.8.: Results for the robustness check regarding firms' productivity in terms of patents

	OLS estimates		selection-corrected estimates	
	Coef. **Std.Err.**	**Coef.** **Std.Err.**	**Coef.** **Std.Err.**	**Coef.** **Std.Err.**
venture capital	0.215** (0.099)		0.238** (0.108)	
private vc		0.346* (0.202)		0.359* (0.210)
cont. R&D	0.082*** (0.026)	0.091*** (0.027)	0.093*** (0.031)	0.084*** (0.029)
patent_ before	0.795*** (0.199)	0.777*** (0.182)	0.845*** (0.243)	0.904*** (0.287)
m_ graduate	0.018 (0.024)	0.018 (0.025)	0.040 (0.036)	0.079 (0.061)
m_ technical	0.024 (0.024)	0.026 (0.024)	0.027 (0.025)	0.021 (0.021)
log(initial size)	0.031 (0.025)	0.031 (0.024)	0.038 (0.035)	0.048 (0.040)
good rating	-0.059 (0.041)	-0.052 (0.040)	-0.047 (0.048)	-0.055 (0.041)
medium rating	-0.037 (0.045)	-0.035 (0.044)	-0.024 (0.054)	-0.014 (0.057)
m_ majority	0.029 (0.030)	0.033 (0.029)	0.011 (0.042)	-0.024 (0.070)
log(distance)	-0.013 (0.011)	-0.014 (0.011)	-0.013 (0.011)	-0.015 (0.011)
constant	0.019 (0.063)	0.012 (0.064)	-0.113 (0.254)	-0.247 (0.321)
industry dummies	included	included	included	included
foundation years	included	included	included	included
λ			0.045 (0.073)	0.086 (0.096)
log Likelihood	-358.89	-355.01	-354.35	-351.10
F(all) [a]	4.07***	114.51***	4.00***	4.13***
F(industries) [b]	1.71	2.02*	1.84	1.75
F(foundation years) [b]	0.92	0.86	0.95	0.69
adjusted R^2	0.230	0.237	0.234	0.239
BIC	-5,020.93	-4,891.79	-4,915.27	-4,898.29
Number of observations	869	869	869	869

This table depicts coefficients of OLS regressions and two-step selection models regarding the average number of patents per year. These findings are intended to provide hints regarding the patent productivity of firms.

[a] F(all) displays a F-test of the joint significance of all variables.

[b] F(industries) and F(foundation years) display F-tests on the joint significance of industry and foundation year dummies.

Table B.9.: Results for FIML count data model accounting for endogeneity of private VC financing

Model	**Poisson**		**Negative Binomial**	
	Patent equation	**Switching eq.**	**Patent equation**	**Switching eq.**
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
private vc	0.140 (0.197)		2.203*** (0.243)	
cont. R&D	1.931*** (0.165)	-0.052 (0.204)	2.227*** (0.203)	-0.060 (0.208)
pat_ before	3.065*** (0.220)	1.494*** (0.322)	4.314*** (0.324)	1.548*** (0.337)
m_ graduate [a]	0.501** (0.217)	0.704** (0.311)	0.887*** (0.222)	0.738** (0.309)
m_ technical [a]	-0.075 (0.175)	-0.072 (0.194)	-0.605* (0.348)	-0.055 (0.196)
m_ majority [a]	0.557*** (0.138)	-0.583** (0.287)	0.231 (0.244)	-0.597** (0.282)
log(initial size) [a]	0.487*** (0.078)	0.128 (0.118)	0.166* (0.098)	0.111 (0.118)
good rating [a]	-0.233 (0.198)	0.057 (0.334)	-0.377 (0.268)	0.035 (0.335)
medium rating [a]	-0.355** (0.176)	0.239 (0.297)	-0.515** (0.208)	0.233 (0.297)
log(distance)	-0.136*** (0.034)		0.026 (0.066)	
East Germany	0.788*** (0.173)	0.067 (0.235)	-0.656** (0.282)	0.000 (0.238)
log(number team)		0.319 (0.198)		0.308 (0.198)
m_ industry experience		0.171 (0.238)		0.193 (0.242)
intermediate		0.188 (0.191)		0.242 (0.190)
constant	-4.653*** (0.407)	-2.965*** (0.566)	-3.674*** (0.821)	-3.004*** (0.571)
industry dummies	included	included	included	included
foundation year dummies	included	included	included	included
$\hat{\sigma}$	1.595 (0.790)		2.143 (0.126)	
$\hat{\rho}$	0.221 (0.137)		0.271 (0.126)	
$\hat{\alpha}$			0.018 (0.186)	
Log likelihood	-560.57		-499.26	
LR(endogeneity) [a]	442.42***		92.50***	
χ^2*(all)* [b]	736.69***		448.50***	
χ^2*(industries)* [c]	17.19**		28.06***	
χ^2*(foundation years)* [c]	85.08***		58.22***	
χ^2*(instruments)* [d]	4.21		4.81	
McFadden's R^2	0.397		0.310	
McFadden's adjusted R^2	0.346		0.244	
Cragg-Uhler's R^2	0.648		0.504	
BIC	-4,441.61		-4,334.34	
Number of observations	869		869	

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts coefficients of an endogenous switching count model which corrects for the endogeneity of the binary variable VC financing in the count model by estimating simultaneously a Poisson (Negbin) model and a probit type VC equation by a full-information maximum likelihood model according to Terza (1998).

[a] LR(endogeneity) displays a LR-test of the two models showing that the endogeneity-corrected model is supposed to be the true one. The LR-tests are calculated using the log likelihoods of the standard Poisson and Negbin models.

[b] χ^2(all) displays a test of the joint significance of all variables.

[c] χ^2(industries) and χ^2(foundation years) display tests of the joint significance of industry and foundation year dummies respectively.

[d] χ^2(instruments) displays a test of the joint significance of instrumental variables in the VC equation.

Table B.10.: Results for FIML multinomial logit accounting for endogeneity of private VC financing

	Multinomial logit for innovativeness			**Switching eq.**
Model	**self**	**others**	**innovative**	
	Coeff. (Std.Err.)	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**	**Coeff. (Std.Err.)**
private vc	6.215*** (2.069)	-6.552*** (2.055)	1.745 (1.921)	
cont. R&D	3.381*** (0.689)	-0.520 (0.629)	1.254** (0.563)	0.147 (0.165)
m_ graduate	0.674* (0.404)	-1.368** (0.553)	0.294 (0.377)	0.718*** (0.175)
m_ technical	0.782** (0.341)	0.455 (0.365)	0.794*** (0.303)	0.240 (0.174)
m_ majority	0.327 (0.376)	-1.160** (0.474)	0.192 (0.342)	-0.655*** (0.171)
log(initial size)	0.242 (0.212)	0.015 (0.229)	-0.121 (0.191)	-0.222** (0.090)
good rating	-0.466 (0.567)	0.442 (0.654)	-0.248 (0.522)	-0.195 (0.257)
medium rating	-0.871* (0.521)	0.351 (0.590)	-0.534 (0.477)	0.231 (0.187)
log(distance)	0.005 (0.097)	-0.028 (0.092)	-0.041 (0.085)	
East Germany	-0.111 (0.509)	0.938* (0.527)	0.467 (0.445)	0.038 (0.178)
number team				0.664*** (0.132)
m_ indexp				0.431*** (0.132)
pat_ before				1.895*** (0.275)
intermediate				0.344*** (0.115)
constant	-1.792** (0.880)	-0.535 (0.935)	-0.371 (0.761)	-3.357*** (0.356)
industry dummies	included	included	included	included
foundation year dummies	included	included	included	included
ν	-1.192* (0.723)	2.586*** (0.765)	-2.317*** (0.728)	
Log likelihood		-1,029.76		
LR(endogeneity) [a]		80.86***		
χ^2*(industries)* [b]		14.50		
χ^2*(foundation year)* [c]		69.86***		
χ^2*(instruments)* [d]		82.51***		
BIC		-2,875.39		
Number of observations		872		

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.

This table depicts coefficients of an endogenous switching multinomial logit model as proposed in Terza (2002) which corrects for the endogeneity of the binary variable private VC financing in the multinomial logit by estimating simultaneously a multinomial logit model and a probit type VC equation by full-information maximum likelihood.

[a] LR(endogeneity) displays a LR-test of the two models showing that the endogeneity-corrected model is supposed to be the true one.

[b] χ^2(industries) displays a test of the joint significance of industry dummies.

[c] χ^2(foundation year) displays a test of the joint significance of foundation year dummies.

[d] χ^2(instruments) displays a test of the joint significance of instrumental variables in the VC equation. Clearly, the instruments are jointly significant.

C. Appendix: Innovation and R&D decision and business cycle

Table C.1.: Classification of Industry

Dummy	Description	NACE
industry dummy 1	Food, beverage and tobacco	15, 16
industry dummy 2	Textile, clothes and leather goods	17,18,19
industry dummy 3	Wood, paper, publishing, printing, furniture, jewellery, musical and sport instruments, toys and others	20, 21, 22, 36
industry dummy 4	Fuels, chemicals, rubber and plastic products	23, 24, 25
industry dummy 5	Non-metallic mineral products, basic metals and fabricated metals	26, 27, 28
industry dummy 6	Machinery and equipment	29
industry dummy 7	Office, data processing, electrical machinery and components, communication equipment and medical, optical instruments and watches	30, 31, 32, 33
industry dummy 8	Motor vehicles and components and other transports	34, 35

Table C.2.: Size cluster defined by number of employees

No.	**Size cluster**	**No.**	**Size cluster**
1	5 - 9	5	100 - 199
2	10 - 19	6	200 - 499
3	20 - 49	7	500 - 1,000
4	50 - 99		

Table C.3.: Specifying the appropriate business cycle indicator and lag structure using BIC (SMEs)

Lag structure [a]	**lack qual. labor**	**exp. busi. dev.**	**capacity**
non-innovating → innovating			
Lagged 1 period	-10,143.42	-10,144.55	-10,142.87
Lagged 2 periods	-10,136.29	-10,140.36	-10,136.57
Lagged 3 periods	-10,130.63	-10,137.47	-10,129.99
Lagged 4 periods	-10,124.97	-10,131.16	-10,122.59
Lagged 5 periods	-10,117.66	-10,125.24	-10,115.21
Lagged 6 periods	-10,110.29	-10,118.52	-10,108.64
Lagged 7 periods	-10,103.07	-10,114.33	-10,102.40
innovating → innovating			
Lagged 1 period	-12,939.66	-12,947.00	-12,939.23
Lagged 2 periods	-12,932.80	-12,941.41	-12,934.28
Lagged 3 periods	-12,925.21	-12,940.68	-12,927.85
Lagged 4 periods	-12,917.84	-12,933.84	-12,920.45
Lagged 5 periods	-12,913.99	-12,927.07	-12,921.59
Lagged 6 periods	-12,917.00	-12,922.48	-12,920.03
Lagged 7 periods	-12,909.68	-12,916.22	-12,914.80
non-researching → researching			
Lagged 1 period	-11,184.36	-11,189.45	-11,189.11
Lagged 2 periods	-11,181.36	-11,184.08	-11,184.15
Lagged 3 periods	-11,176.19	-11,181.66	-11,178.69
Lagged 4 periods	-11,171.19	-11,175.63	-11,173.29
Lagged 5 periods	-11,171.17	-11,176.97	-11,166.18
Lagged 6 periods	-11,163.77	-11,172.23	-11,159.52
Lagged 7 periods	-11,156.79	-11,164.87	-11,152.42
researching → researching			
Lagged 1 period	-9,053.66	-9,058.51	-9,051.85
Lagged 2 periods	-9,047.31	-9,055.55	-9,048.80
Lagged 3 periods	-9,042.72	-9,048.95	-9,044.65
Lagged 4 periods	-9,044.05	-9,043.57	-9,054.35
Lagged 5 periods	-9,036.86	-9,048.26	-9,059.82
Lagged 6 periods	-9,037.88	-9,068.35	-9,067.87
Lagged 7 periods	-9,036.91	-9,062.14	-9,066.16

This table depicts the BICs of regressions run in order to find out which is the appropriate business cycle representation and the corresponding lag structure. We also tested the lag structure of the variables *real standard wages* and *real interest rates*. The lag structure of those variables turns out to be not existent. Therefore, the BICs are not displayed. The BICs for small firms are exactly the same, so we do not display the BICs here.

[a] All BICs reflect regressions including the lagged differences of the respective variable as well as the previous lags.

Table C.4.: Regression results for Markov chains with heterogeneity regarding firm and departure state (innovation activities)

	non-innovating → innovating		innovating → innovating	
	all firms	SMEs	all firms	SMEs
	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)
Δ *exp. business develop.*	-0.468	-0.463	-0.765***	-1.012***
	(0.285)	(0.366)	(0.264)	(0.355)
Δ *real standard wage*	0.470*	0.902***	-0.389*	-0.688**
	(0.258)	(0.347)	(0.234)	(0.339)
Δ *real interest rate*	-4.158***	-4.687**	-0.824	1.027
	(1.393)	(1.858)	(1.172)	(1.561)
Δ *pcm*	-0.507**	-0.398	0.017	0.124
	(0.203)	(0.249)	(0.174)	(0.219)
pcm_2	1.255***	0.324	2.418***	0.230
	(0.218)	(0.292)	(0.133)	(0.240)
pcm_3	1.412***	0.496	2.499***	0.342
	(0.224)	(0.304)	(0.138)	(0.245)
pcm_4	1.509***	0.439	2.209***	0.118
	(0.277)	(0.375)	(0.198)	(0.306)
Δ *log(employees)*	0.989***	0.701*	-0.471	0.201
	(0.350)	(0.415)	(0.290)	(0.362)
size_2	0.611***	0.680***	0.582***	0.644***
	(0.156)	(0.177)	(0.145)	(0.161)
size_3	0.706***	0.785***	0.705***	0.597***
	(0.157)	(0.203)	(0.132)	(0.167)
size_4	1.027***		1.032***	
	(0.175)		(0.139)	
Δ *diversification*	-0.002	0.002	-0.601**	-0.689*
	(0.349)	(0.436)	(0.273)	(0.354)
Herfindahl(t-1)	-0.412	-1.506	1.930*	3.018*
	(1.290)	(1.714)	(1.055)	(1.593)
market share(t-1)	0.080	0.045	0.034	0.650
	(0.066)	(0.310)	(0.041)	(0.612)
human capital(t-1)	1.055	2.066**	1.698***	1.862**
	(0.698)	(0.833)	(0.582)	(0.757)

(To be continued on next page)

	non-innovating → innovating		innovating → innovating	
	all firms	**SMEs**	**all firms**	**SMEs**
	Coef. (Std.Err.)	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**
export intensity(t-1)	0.341**	0.439**	-0.756***	-0.375*
	(0.173)	(0.216)	(0.158)	(0.225)
log(product life cycle(t-1))	-0.094	-0.134*	-0.110*	-0.224***
	(0.062)	(0.074)	(0.065)	(0.083)
East Germany	-0.010	0.062	0.264**	0.161
	(0.127)	(0.145)	(0.113)	(0.133)
constant	-2.661***	-1.870***	-1.224***	1.104**
	(0.386)	(0.504)	(0.307)	(0.465)
industry dummies	*included*	*included*	*included*	*inc luded*
$\hat{\sigma}_{j1}$	0.252	-0.583	0.014	-0.066
	(0.266)	(0.379)	(0.240)	(0.263)
log Likelihood	-1,238.45	-879.07	-1,679.60	-944.07
χ^2(all) [a]	134.95***	50.68***	500.73***	93.62***
χ^2(industries) [b]	9.95	3.43	35.36***	16.34**
McFadden's R^2	0.052	0.028	0.130	0.047
McFadden's adjusted R^2	0.031	-0.001	0.116	0.021
Cragg-Uhler's R^2	0.084	0.046	0.194	0.073
BIC	-15,143.81	-10,155.87	-27,537.60	-12,944.39
number of observations	2,303	1,636	3,778	1,980

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts coefficients of logit-type models estimating the impact factors on firms' R&D transition accounting for heterogeneity regarding firm and departure state. The heterogeneity term σ_{j1} is estimated. Standard errors are clustered by firm.

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(industries) displays a test of the joint significance of industry dummies.

Table C.5.: Regression results for Markov chains with heterogeneity regarding firm and transition (innovation activities)

	non-innovating → innovating		innovating → innovating	
	all firms	SMEs	all firms	SMEs
	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)
Δ *exp. business develop.*	-0.478	-0.492	-0.767***	-1.021***
	(0.295)	(0.379)	(0.265)	(0.357)
Δ *real standard wage*	0.483*	0.955***	-0.386*	-0.689**
	(0.266)	(0.369)	(0.235)	(0.341)
Δ *real interest rate*	-4.242***	-4.836**	-0.831	0.997
	(1.441)	(1.895)	(1.172)	(1.570)
Δ *pcm*	-0.519**	-0.413	0.018	0.123
	(0.210)	(0.260)	(0.174)	(0.221)
pcm_2	1.286***	0.332	2.421***	0.229
	(0.227)	(0.304)	(0.135)	(0.241)
pcm_3	1.445***	0.513	2.501***	0.342
	(0.231)	(0.315)	(0.140)	(0.247)
pcm_4	1.553***	0.454	2.212***	0.119
	(0.290)	(0.389)	(0.199)	(0.309)
Δ *log(employees)*	1.022***	0.719*	-0.467	0.216
	(0.362)	(0.431)	(0.291)	(0.365)
size_2	0.631***	0.697***	0.582***	0.651***
	(0.164)	(0.183)	(0.145)	(0.162)
size_3	0.729***	0.833***	0.706***	0.604***
	(0.164)	(0.216)	(0.132)	(0.170)
size_4	1.055***		1.032***	
	(0.184)		(0.139)	
Δ *diversification*	-0.021	-0.016	-0.601**	-0.688*
	(0.359)	(0.454)	(0.273)	(0.356)
Herfindahl(t-1)	-0.418	-1.729	1.936*	3.019*
	(1.330)	(1.804)	(1.057)	(1.602)
market share(t-1)	0.086	0.056	0.034	0.651
	(0.068)	(0.333)	(0.041)	(0.617)
human capital(t-1)	1.087	2.156**	1.699***	1.871**
	(0.720)	(0.883)	(0.582)	(0.764)

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	non-innovating → innovating		innovating → innovating	
	all firms	**SMEs**	**all firms**	**SMEs**
	Coef. (Std.Err.)	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**
export intensity(t-1)	0.344*	0.467**	-0.756***	-0.371
	(0.179)	(0.226)	(0.158)	(0.227)
log(product life cycle(t-1))	-0.095	-0.140*	-0.110*	-0.226***
	(0.064)	(0.077)	(0.065)	(0.084)
East Germany	-0.016	0.067	0.264**	0.162
	(0.130)	(0.151)	(0.113)	(0.134)
constant	-2.746***	-1.920***	-1.225***	1.108**
	(0.411)	(0.514)	(0.308)	(0.466)
industry dummies	*included*	*included*	*included*	*included*
$\hat{\sigma}_{j0}$	0.403	-0.574*	-0.071	0.209
	(0.273)	(0.318)	(0.248)	(0.271)
$\hat{\sigma}_{j1}$	0.251	-0.517	0.011	-0.047
	(0.283)	(0.389)	(0.237)	(0.277)
log likelihood	-1,237.33	-877.39	-1,679.56	-943.82
χ^2(all) [a]	116.62***	51.42***	487.82***	89.35***
χ^2(industries) [b]	9.71	3.27	35.24***	16.18**
McFadden's R^2	0.045	0.028	0.127	0.045
McFadden's adjusted R^2	0.023	-0.001	0.112	0.018
Cragg-Uhler's R^2	0.073	0.046	0.190	0.070
BIC	-15,138.32	-10,151.83	-27,529.44	-12,937.29
number of observations	2,303	1,636	3,778	1,980

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts coefficients of logit-type models estimating the impact factors on firms' R&D transition accounting for heterogeneity regarding firm and departure state. The heterogeneity terms σ_{j0} and σ_{j1} are estimated. Standard errors are clustered by firm.

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(industries) displays a test of the joint significance of industry dummies.

Table C.6.: Results for Markov chains with heterogeneity regarding departure state (R&D activities)

	non-researching → researching		researching → researching	
	all firms	**SMEs**	**all firms**	**SMEs**
	Coef. (Std.Err.)	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**
Δ *exp. business develop.*	-0.936*** (0.345)	-1.281*** (0.449)	-1.839*** (0.510)	-1.565*** (0.598)
Δ*2 exp. business develop.*			0.325 (0.410)	0.741 (0.512)
Δ*3 exp. business develop.*			0.074 (0.456)	-0.217 (0.559)
Δ*4 exp. business develop.*			0.377 (0.495)	0.555 (0.638)
Δ*5 exp. business develop.*			-0.310 (0.469)	-0.512 (0.555)
Δ*6 exp. business develop.*			-2.467*** (0.441)	-2.787*** (0.618)
Δ *real standard wage*	0.847*** (0.319)	1.095** (0.436)	-1.007* (0.547)	-0.609 (0.703)
Δ *real interest rate*	-5.700*** (1.642)	-5.991*** (2.194)	2.579 (2.410)	3.169 (3.005)
Δ *pcm*	-0.057 (0.260)	0.107 (0.335)	0.607** (0.306)	0.654* (0.372)
pcm_2	0.719*** (0.276)	0.336 (0.350)	1.560*** (0.321)	0.759* (0.401)
pcm_3	0.620** (0.284)	0.292 (0.362)	1.402*** (0.322)	0.591 (0.395)
pcm_4	0.685** (0.343)	-0.025 (0.456)	1.449*** (0.408)	0.435 (0.501)
Δ *log(employees)*	0.046 (0.422)	-0.149 (0.496)	0.676 (0.572)	1.278* (0.714)
size_2	0.608*** (0.191)	0.725*** (0.213)	0.444* (0.236)	0.443* (0.254)
size_3	0.936*** (0.195)	0.924*** (0.259)	0.819*** (0.239)	0.516* (0.297)

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	non-researching → researching		**researching → researching**	
	all firms	**SMEs**	**all firms**	**SMEs**
	Coef. (Std.Err.)	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**
size_4	1.197***		1.298***	
	(0.223)		(0.260)	
Δ *diversification*	-0.308	-0.101	-1.465***	-1.099*
	(0.405)	(0.485)	(0.530)	(0.612)
Herfindahl(t-1)	-0.947	-0.410	3.088	5.315*
	(1.581)	(2.041)	(1.907)	(2.812)
market share(t-1)	0.109	0.179	0.253**	2.155*
	(0.100)	(0.489)	(0.108)	(1.190)
human capital(t-1)	1.856**	2.451***	1.589	0.931
	(0.770)	(0.940)	(1.047)	(1.240)
export intensity(t-1)	0.397*	0.588**	0.823**	0.335
	(0.219)	(0.264)	(0.370)	(0.451)
log(product life cycle(t-1))	0.001	-0.056	-0.082	0.003
	(0.074)	(0.092)	(0.112)	(0.132)
East Germany	0.192	0.350*	0.946***	0.872***
	(0.157)	(0.180)	(0.217)	(0.238)
constant	-3.216***	-2.955***	-0.471	-0.326
	(0.486)	(0.648)	(0.558)	(0.710)
industry dummies	*included*	*included*	*included*	*inc luded*
$\hat{\sigma}_{j1}$	0.353	-0.788*	0.942**	-0.707
	(0.355)	(0.463)	(0.440)	(0.698)
log Likelihood	-893.32	-633.62	-749.08	-433.10
χ^2(all) [a]	90.96***	46.69***	87.40***	55.11***
χ^2(industries) [b]	18.28**	12.37	39.80***	21.17***
McFadden's R^2	0.048	0.036	0.055	0.060
McFadden's adjusted R^2	0.020	-0.004	0.015	-0.007
Cragg-Uhler's R^2	0.070	0.050	0.071	0.079
BIC	-15,206.65	-11,201.47	-20,294.05	-9,141.64
number of observations	2,231	1,702	2,780	1,411

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts coefficients of logit-type models estimating the impact factors on firms' R&D transition accounting for heterogeneity regarding firm and departure state. The heterogeneity term σ_{j1} is estimated. Standard errors are clustered by firm.

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(industries) displays a test on the joint significance of industry dummies.

Table C.7.: Results for Markov chains with heterogeneity regarding transition (R&D activities)

	non-researching → researching		researching → researching	
	all firms	**SMEs**	**all firms**	**SMEs**
	Coef. (Std.Err.)	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**	**Coef. (Std.Err.)**
Δ *exp. business develop.*	-0.972*** (0.353)	-1.280*** (0.448)	-1.854*** (0.521)	-1.777** (0.744)
$\Delta 2$ *exp. business develop.*			0.325 (0.414)	0.926 (0.690)
$\Delta 3$ *exp. business develop.*			0.072 (0.460)	-0.430 (0.795)
$\Delta 4$ *exp. business develop.*			0.374 (0.500)	0.665 (0.781)
$\Delta 5$ *exp. business develop.*			-0.302 (0.473)	-0.642 (0.702)
$\Delta 6$ *exp. business develop.*			-2.488*** (0.463)	-3.434*** (1.284)
Δ *real standard wage*	0.860*** (0.327)	1.096** (0.435)	-1.009* (0.553)	-0.663 (0.828)
Δ *real interest rate*	-5.885*** (1.689)	-5.998*** (2.194)	2.673 (2.457)	3.276 (3.526)
Δ *pcm*	-0.067 (0.266)	0.108 (0.335)	0.628** (0.315)	0.777 (0.488)
pcm_2	0.725*** (0.279)	0.336 (0.350)	1.577*** (0.333)	0.976* (0.574)
pcm_3	0.626** (0.288)	0.293 (0.362)	1.415*** (0.333)	0.760 (0.540)
pcm_4	0.691** (0.348)	-0.024 (0.455)	1.468*** (0.424)	0.616 (0.649)
Δ *log(employees)*	0.039 (0.429)	-0.148 (0.496)	0.690 (0.579)	1.504* (0.910)
size_2	0.614*** (0.196)	0.724*** (0.214)	0.450* (0.241)	0.543 (0.368)
size_3	0.957*** (0.199)	0.923*** (0.260)	0.831*** (0.248)	0.673 (0.449)
size_4	1.220*** (0.227)		1.313*** (0.271)	

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	non-researching → researching		researching → researching	
	all firms	SMEs	all firms	SMEs
	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)	Coef. (Std.Err.)
Δ diversification	-0.325	-0.100	-1.484***	-1.295
	(0.412)	(0.485)	(0.542)	(0.801)
Herfindahl(t-1)	-0.980	-0.411	3.165	5.762*
	(1.611)	(2.042)	(1.956)	(3.328)
market share(t-1)	0.103	0.178	0.255**	2.436*
	(0.102)	(0.489)	(0.110)	(1.351)
human capital(t-1)	1.919**	2.449***	1.601	1.141
	(0.796)	(0.941)	(1.052)	(1.500)
export intensity(t-1)	0.416*	0.588**	0.826**	0.369
	(0.225)	(0.264)	(0.374)	(0.544)
log(product life cycle(t-1))	0.001	-0.056	-0.081	-0.003
	(0.075)	(0.092)	(0.113)	(0.156)
East Germany	0.198	0.350*	0.953***	1.000***
	(0.160)	(0.180)	(0.220)	(0.352)
constant	-3.298***	-2.953***	-0.475	-0.401
	(0.500)	(0.651)	(0.563)	(0.858)
industry dummies	*included*	*included*	*included*	*included*
$\hat{\sigma}_{j0}$	-0.403	-0.027	0.188	0.873*
	(0.282)	(0.268)	(0.337)	(0.507)
$\hat{\sigma}_{j1}$	0.327	-0.784*	0.967**	-1.164
	(0.334)	(0.473)	(0.490)	(1.078)
log likelihood	-892.39	-633.61	-748.94	-431.22
χ^2(all) [a]	90.03***	46.10**	74.04***	21.17***
χ^2(industries) [b]	18.34**	12.33*	36.68***	10.15
McFadden's R^2	0.048	0.035	0.047	0.024
McFadden's adjusted R^2	0.018	-0.006	0.005	-0.048
Cragg-Uhler's R^2	0.070	0.050	0.061	0.032
BIC	-15,200.81	-11,194.04	-20,286.40	-9,138.15
number of observations	2,231	1,702	2,780	1,411

*** (**, *) indicate significance of 1 % (5 %, 10 %) respectively.
This table depicts coefficients of logit-type models estimating the impact factors on firms' R&D transition accounting for heterogeneity regarding firm and departure state. The heterogeneity terms σ_{j0} and σ_{j1} are estimated. Standard errors are clustered by firm.

[a] χ^2(all) displays a test of the joint significance of all variables.

[b] χ^2(industries) displays a test on the joint significance of industry dummies.